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 SoK 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.

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 problem: what is the root cause that enables social engineering attacks? In order to answer these questions, we need to narrow down the scope, since human factors are such a broad topic. 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 this problem 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. [2019], Khonji et al. [2013], Zaimi et al. [2020], Dou et al. [2017], Almomani et al. [2013], Basit et al. [2020], Ali et al. [2020], Jain and Gupta [2021], Sahu and Dubey [2014], da Silva et al. [2020], Alabdan [2020], Vrjayalakshmi et al. [2020], Jampen et al. [2020], Chanti and Chithralekha [2020], Rastenis et al. [2020], Gupta et al. [2018], Chiew et al. [2018], Aleroud and Zhou [2017], Yasin et al. [2019], Montañez et al. [2020], Gupta et al. [2016], Heartfield and Loukas [2015], Alharthi et al. [2020], Salahdine and Kaabouch [2019] and the extensive list of references therein). It is also shown by the scale of financial losses incurred by these attacks; for example, FBI reports a $26B loss between June 2017 and July 2019 associated with attack emails that contain instructions on approving payments to attackers and pretend to come from executives [FBI [2020]]. However, our examination shows that prior studies focus on technical solutions which mainly leverage Artificial Intelligence/Machine Learning (AI/ML) to design various kinds of defense systems. This may be understood as follows: Since these attacks often leverage information technology as a means to wage attacks (e.g., many attacks do not have counterparts in the era prior to the emergence of cyberspace), it has been largely treated as a technological problem. This is evidenced by the fact that most existing defenses against them leverage AI/ML techniques. As a result, very few studies take a close look at the root causes of social engineering techniques; the present study fills this void.

Our Contributions. In this paper we systematize Internet-based social engineering attacks through the lens of psychology. 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. 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 in a sense 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 is inspired by the well-known, generic human information processing framework of “System 1 vs. System 2”, but offers ingredients that are particularly relevant to cybersecurity. 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 resulting quantitative understanding will guide us to design effective defenses.

Related Work. Table 1 contrasts the present SoK 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 to put the present study in context, and describes our SoK methodology. Section 3 systematizes PFs and PTs. Section 4 systematizes social engineering attacks. Section 5 systematizes defenses against social engineering attacks. Section 6 further systematizes the knowledge at a higher level of abstraction by introducing a mapping across PFs, PTs, attacks, and defenses, and presenting a roadmap for future research directions. Section 7 concludes the present study.

2 Psychological Preparation and Methodology

2.1 Psychological Background Knowledge

We briefly review the psychological background knowledge that would be helpful for understanding the present paper.

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, AGREABLENESS, 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]. 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, 2001], [Cialdini and James, 2009], are LIKING which denotes being easily influenced by those one likes or those with common beliefs as them; RECIPROCATION which denotes feeling obliged to return a favor; SOCIAL PROOF (conformity) which denotes imitating the behaviours of others; CONSISTENCY (commitment) which denotes consistency of behaviour or sticking to a promise; AUTHORITY, which denotes submitting to experts or obeying orders from one’s superior or authoritative figures; and 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 Trost, 1998]
SoK: Why Have Defenses against Social Engineering Attacks Achieved Limited Success?

A P

Ref.

Psychological Factors (PFs)  Psychological Techniques (PTs)  Attacks  Defenses  Map

Das et al. [2019]  √ (6)  √  √  
Khonji et al. [2013]  √  √  
Zaimi et al. [2020]  √  √  
Dou et al. [2017]  √  √  
Almomani et al. [2013]  √  √  
Basit 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]  √  √  
Rastemis et al. [2020]  √  
Gupta et al. [2018]  √  √  
Chew et al. [2018]  √  
Aleroud and Zhou [2017]  √  √  
Yasin et al. [2019]  √  
Montanaz et al. [2020]  √ (19)  √  
Gupta et al. [2016]  √  √  
Heartfield and Loukas [2015]  (2)  √  √  
Alarthi et al. [2020]  √  √  
Salahdine and Kaabouch [2019]  √ (41)  (13)  √  √  √  
Ours  √  √  √  

Table 1: Comparison of existing surveys and our SoK, where parentheses show the number of factors or techniques discussed in a paper. Only Montañez et al. [2020] and ours systematized PFs; the other studies merely mention some factors.

persuasion is detected, it results in a negative response towards the message Kirmani and Zhu [2007]. The use of persuasion in social engineering messages has been studied extensively 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.

Human Information Processing: System 1 vs. System 2. The human mind processes information from the environment through a variety of cognitive mechanisms. Human information processing is often understood as a dual-processing system involving two processing routes: System 1 (heuristic) and System 2 (analytic). System 1 is fast, effortless, based on heuristics, and often thought of as error-prone; System 2 is slow, effortful, and involves deep analytical thinking. This framework has become quite popular in psychology and beyond Kahneman [2011]. 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 in order to build a more robust framework later in the paper.

2.2 Systematization 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.

Motivation. We aim to understand (i) the cause of defenses’ inability to robustly mitigate social engineering attacks and (ii) how a solution might be found in future studies. We hope to solve these problems with a systematic characterization of attacks and defenses with respect to PFs that contribute to human susceptibility to social engineering attacks.
Methodology. In order to identify the relevant literature, we use the keywords social engineering and phishing to find research papers in the following literature databases: IEEE (including S&P), ACM (including CCS), Usenix (including Security), and NDSS, Elsevier, Springer, PlosOne, Wiley, and Emerald. In addition, we search Journals like Frontiers in Psychology and Information & Computer Security (ICS). This broad search is to accommodate the fact that many studies on Internet-based social engineering attacks may not be published in mainstream security venues. The search identified 457 papers, which were manually examined based on their treatment and relevance to the motivation and scope of the present study as mentioned above, leading to 134 papers which include 24 survey/review papers.

Having identified the literature for systematization, we proceed as follows. First, we use our psychological expertise to identify the PFs that would affect individuals’ susceptibility to social engineering attacks, while leveraging the literature (e.g., the impact of a factor on individuals’ susceptibility is positive or negative). Second, we systematize known attacks with respect to those factors (e.g., the PF(s) exploited by an attack and the extent to which a factor’s impact on human susceptibility has been quantified). Third, we systematize known defenses with respect to those PFs (e.g., the factor leveraged by a defense and the extent to which the a defense’s effectiveness is quantified). Fourth, we present mappings across PFs, PTs, attacks and defenses, in order to give a succinct representation of the state-of-the-art knowledge in this domain. This 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.

3 Human Psychological Factors and Techniques

In order to understand why humans are susceptible to social engineering attacks, we systematize the PFs and PTs that have been, or could be, exploited by social engineering 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); whereas, the term PT is used to describe how attacks exploit these factors. This distinction is important because the PTs will be leveraged to build a “bridge” for mapping social engineering attacks to PFs. Note that one PT can exploit multiple PFs and vice versa.

3.1 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 cognition 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 Hills [McAlaney and Hills 2020] argued that people are motivated tacticians and will apply a cognitive miser (or naive 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. 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. 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. Absentminded people can easily click on phishing links because they do not pay attention to what they are doing [Zafar et al. 2019].

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 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 [Siadat et al. 2017] and is often paired with need [Ferreira 2018].

2. **Fear.** This PF describes one’s belief that something painful, dangerous or threatening may happen. It is relevant because situations that evoke fear bring about a strong avoidance reaction in both behavioral responses and cognitive processing [Ness et al. 2017]. Algarni et al. [Algarni et al. 2017] found that social engineering attacks are effective against people who submit to fear toward, and orders from, influential people.

3. **Sympathy.** This is the emotional state of individuals who understand the mental or emotional state of another person without actually feeling the same emotion [Williams et al. 2017].

4. **Empathy.** This PF describes the emotional state of an individual who personally relates to the mental or emotional state of another person based on their own experiences with the same state. It is widely exploited by scammers to get what they want from their victims [Williams et al. 2017].

5. **Loneliness.** This PF describes one’s subjective perception of discrepancy between the desired and the actual social companionship, connectedness, or intimacy [Buecker et al. 2020]. A study of 299 participants [Deutrom et al. 2021] found that loneliness positively predicts problematic internet uses that can be exploited by social engineering attacks.

The preceding discussion suggests that *emotion* PFs have been widely exploited by attacks. However, there is no deep or quantitative understanding of their impact on individuals’ susceptibility to 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. Social engineering attackers use **Authority** to lure their victims to divulge confidential information, especially through spear phishing [Zheng et al. 2019]. In 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]. Bullée et al. [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]. Bullée et al. [Bullée et al. 2018] found that Liking is widely exploited by social engineering attacks. Hatfield [Hatfield 2018] also 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. This PF has been widely exploited in online scams [Williams et al. 2017], [Bullée et al. 2018] and 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]. 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 ideal. Social engineering attacks use commitment to persuade their victims. Algani 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.
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)]

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. (2019)]

The preceding discussion suggests the following PFs have been widely exploited by social engineering attacks: **Authority, Scarcity, Liking (Similarity), and Reciprocation.** 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. Li et al. [Li et al. (2019)] found 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 are predisposed to trust others they view as likable and phishers make use of this PF to scam victims. [Hatfield (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)]

7. **Vulnerability.** This PF describes the degree to which one is in need of special care, support, or protection because of age, disability, or risk of abuse or neglect. In a study aiming to identify those at greater risk of falling victim to social engineering attacks in an organization, Bullee et al. [Bullee et al. (2017)] find that employees with one year of service or less are more vulnerable to spear phishing (52.07%) victimization compared to employees with eight years of service (23.19%).

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. [Holt et al. (2020)]. Impatient individuals may be more susceptible to social engineering attacks because they do not carefully examine contents or cues of social engineering attacks, especially when they focus on immediate gratification. [Holt et al. (2020)].

9. **Impulsivity.** This PF describes the tendency of one acting without much thought. [Das et al. (2019)]. In a study with 53 randomly selected participants (undergraduate students), it was found that participants who scored low on impulsivity better managed phishing emails [Welk et al. (2015)]. In another study, it was found that individuals who are sensation-seeking, which is a form of impulsivity, were more likely to become scammed [Whitty (2018)].

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 [Alseadoon et al. (2012)].
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 [Williams et al. 2017] or serve as a persuasion technique to lure their victims [Siadati et al. 2017, Xiangyu et al. 2017].

12. **LAZINESS.** This PF describes the degree of one’s voluntary inability to carry out a task with the energy 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 [Wang et al. 2020].

13. **VIGILANCE.** This PF describes the degree that one is watchful for possible dangers or anomalies. In a phishing experiment with 3000 university students, it was found that vigilance reduced susceptibility to scams [Tu et al. 2019].

14. **OPENNESS.** This PF describes one’s active imagination and insight [Cherry 2012]. 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 [Frauenstein and Flowerday 2020, Das et al. 2019].

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 [Cherry 2012, Frauenstein and Flowerday 2020]. It is found that people with a high conscientiousness are less susceptible to phishing attacks [Halevi et al. 2015].

16. **EXTRAVERSION.** This PF, also known as extraversion, describes the degree to which one is sociable, assertive, talkative, and emotionally expressive [Cherry 2012]. 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 emails [Alseadoon et al. 2015].

17. **AGREEABLENESS.** This PF describes one’s attributes related to trust, altruism, kindness, affection, and other prosocial behaviors [Cherry 2012]. A study found that people with a high agreeableness (and neuroticism, which is described below) are more susceptible to phishing attacks [Yuan et al. 2019].

18. **NEUROTICISM.** This PF describes one’s moodiness and emotional instability. People with high neuroticism often exhibit mood swings, anxiety, irritability, and sadness [Cherry 2012]. Individuals with high neuroticism are more susceptible to phishing attacks [Yuan et al. 2019].

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 2019].

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 2019].

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. **Habituation.** 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.

### 3.2 Psychological Techniques (PTs)

We systematize 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. 2019] 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 [Allodi et al. 2019]: spamdexing (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.

### 4 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.

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

#### 4.2 Attacks

Figure [1] 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.

**Email-based Attacks.** This category includes ten 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). 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.

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]. 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. This attack is often motivated to steal money, get access to systems, steal sensitive information, or for revenge. This attack exploits the **TRUST** factor because it attempts to deceive, for example, a CEO into believing in the content of 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. 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. 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]. This attack is motivated by the objective of stealing money. 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 **malvertising** 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 victims trust the website to be secure, the VULNERABILITY factor when a victim may trust the website in question, 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]. It exploits the TRUST 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 trust 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 often when victims steal money or sensitive information. It exploits the TRUST factor because victims trust 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 ABSEN TM INDEDNESS factor because victims think 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. This attack exploits the LONELINESS factor because lonely people turn to the platform to seek attention [Lin et al. 2019b].

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...” 

[8] www.bankofamerica.com
you if my Internet is suspended". This attack exploits the LIKING AND 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. 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. 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. 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]. 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.

4.3 **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.

5 **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.

5.1 **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.

5.2 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 Dobashi 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].

5.3 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.

5.4 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.
6 Systematization of Knowledge

6.1 Relationships between Attacks, PTs, PFs, and Defenses

Figure 2: Relationships between defenses, attacks, PTs, and PFs. The PFs with empirical quantitative studies are represented with a filled circle and a circle otherwise. The “+” (“-”) sign indicates that a factors increases (decreases) susceptibility; Ind = individual, com = commitment, T = Traditional.

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, 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. Intuitively, social engineering attacks leverage PTs to take effect on PFs. 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.

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 Hacking leverages Trusted Relationship. (10) Tabnabbing leverages Visual Deception and Impersonation. (11) Ad Fraud leverages Persuasion, Incentive and Motivator, Attention Grabbing, and Visual Deception.

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 Trust. (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.

PTs exploiting **cognition PFs** are summarized as follows. (1) Attention Grabbing exploits the ABSENTMINDEDNESS and CURIOSITY factors. (2) Visual Deception exploits OVERCONFIDENCE, TRUST, and HABITUATION.

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.

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).

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.

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 leveraged in defenses against email-based, website-based and OSN-based attacks.

**Summary.** Figure 2 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.

### 6.2 Future Research Directions

The preceding systematization prompts 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.

#### 6.2.1 Creating a Qualitative Psychological Framework Tailored to Social Engineering Attacks

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 3: A qualitative psychological framework describing human information processing of social engineering attacks.

Figure 3 highlights the framework we propose. It is inspired by the state-of-the-art System 1 vs. System 2 framework reviewed in Section 2. 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: risk seeking, risk aversion and 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 [Conway et al. 2017, Howe et al. 2012] and why some people still fall victim even if they recognize the risk [Lea et al. 2009].

**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 heuristic processing or analytic processing, respectively.

- **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 [Abbasi et al. 2016, Redmiles et al. 2018]. 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.

- **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 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 [Kumaraguru et al. 2006].

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.

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

**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 [Dhamija et al. 2006, Kim et al. 2005]. 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.

**Defense Alerts.** These include the mechanisms that are employed to warn users of potential threats to trigger their 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 [Montañez et al. 2020], such as cue salience triggering attention switching [Wogalter 2018]. It is an important open problem to investigate how defenses can influence PFs to offset the influence of attackers.

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

The preceding qualitative framework paves a 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 \(\text{individual\_baseline}, \text{attacker\_effort}, \text{and defense\_alerts}\) are defined above.

### 6.2.3 Designing Effective Defenses

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 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]).

### 7 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.
References

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

Mahmoud Khonji, Youssef Iraqi, and Andrew Jones. Phishing detection: a literature survey. *IEEE Communications Surveys & Tutorials*, 15(4):2091–2121, 2013.

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

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

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

Abdul Basit, Maham Zafar, Xuan Liu, Abdul Rehman Javed, Zunera Jalil, and Kashif Kifayat. A comprehensive survey of ai-enabled phishing attacks technique. *Telecommunication Systems*, pages 1–16, 2020.

Mohammed Mahmood Ali, Mohd S Qaseem, and Md Ateeq Ur Rahman. A survey on deceptive phishing attacks in social networking environments. In *Proceedings of the Third International Conference on Computational Intelligence and Informatics*, pages 443–452. Springer, 2020.

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

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

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

Rana Alabdan. Phishing attacks survey: Types, vectors, and technical approaches. *Future Internet*, 12(10):168, 2020.

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

Daniel Jampen, Gürkan Gür, Thomas Sutter, and Bernhard Tellenbach. Don’t click: towards an effective anti-phishing training. A comparative literature review. *Human-centric Computing and Information Sciences*, 10(1):1–41, 2020.

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

Justinas Rastenis, Simona Ramanauskaite, Justinas Janulevicius, Antanas Ceny, Asa Slotkine, and Kestutis Pakrjauskas. E-mail-based phishing attack taxonomy. *Applied Sciences*, 10(7):2363, 2020.

Brij B Gupta, Nalin AG Arachchilage, and Kostas E Psannis. Defending against phishing attacks: taxonomy of methods, current issues and future directions. *Telecommunication Systems*, 67(2):247–267, 2018.

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

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

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

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

Surbhi Gupta, Abhishek Singhal, and Akanksha Kapoor. A literature survey on social engineering attacks: Phishing attack. In *2016 international conference on computing, communication and automation (ICCCA)*, pages 537–540. IEEE, 2016.

Ryan Heartfield and George Loukas. A taxonomy of attacks and a survey of defense mechanisms for semantic social engineering attacks. *ACM Computing Surveys (CSUR)*, 48(3):1–39, 2015.

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

Fatima Salahdine and Naima Kaabouch. Social engineering attacks: a survey. *Future Internet*, 11(4):89, 2019.
SoK: Why Have Defenses against Social Engineering Attacks Achieved Limited Success? A PREPRINT

FBI. Business email compromise, Apr 2020. URL https://www.fbi.gov/scams-and-safety/common-scams-and-crimes/business-email-compromise

Lewis R Goldberg. Language and individual differences: The search for universals in personality lexicons. Review of personality and social psychology, 2(1):141–165, 1981.

Paul T Costa Jr and Robert R McCrae. The Revised Neo Personality Inventory (neo-pi-r). Sage Publications, Inc, 2008.

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

Robert R McCrae and Oliver P John. An introduction to the five-factor model and its applications. Journal of personality, 60(2):175–215, 1992.

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

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

Robert Cialdini. Principles of persuasion. Arizona State University, eBrand Media Publication, 2001.

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

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

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

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

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

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

Robert Cialdini. Principles of persuasion. Arizona State University, eBrand Media Publication, 2001.

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

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

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

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

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

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

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

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

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

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

Humayun Zafar, Adriane Randolph, Saurabh Gupta, and Carole Hollingsworth. Traditional seta no more: investigating the intersection between cybersecurity and cognitive neuroscience. In Proceedings of the 52nd Hawaii International Conference on System Sciences, 2019.

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

Ana Ferreira. Why ransomware needs a human touch. In 2018 International Carnahan Conference on Security Technology (ICCST), pages 1–5. IEEE, 2018.
Alisha M Ness, Genevieve Johnson, Michael K Ault, William D Taylor, Jennifer A Griffith, Shane Connelly, Norah E Dunbar, and Matthew L Jensen. Reactions to ideological websites: The impact of emotional appeals, credibility, and pre-existing attitudes. Computers in Human Behavior, 72:496–511, 2017.

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

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

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

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

Kangfeng Zheng, Tong Wu, Xiujuan Wang, Bin Wu, and Chunhua Wu. A session and dialogue based social engineering framework. IEEE Access, 2019.

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

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

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

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

Joseph M Hatfield. Social engineering in cybersecurity: The evolution of a concept. Computers & Security, 73:102–113, 2018.

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

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

Henry Collier and Alexandra Collier. The port z3r0 effect! human behaviors related to susceptibility. nature, 2(3):5, 2020.

Elissa M Redmiles, Neha Chachra, and Brian Waiswylde. Examining the demand for spam: Who clicks? In Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems, page 212. ACM, 2018.

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

Tong Li, Kaiyuan Wang, and Jennifer Horkoff. Towards effective assessment for social engineering attacks. In 2019 IEEE 27th International Requirements Engineering Conference (RE), pages 392–397. IEEE, 2019.

Jan-Willem Bullee, Lorena Montoya, Marianne Junger, and Pieter Hartel. Spear phishing in organisations explained. Information & Computer Security, 2017.

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

Allaire K Welk, Kyung Wha Hong, Olga A Zielinska, Rucha Tembe, Emerson Murphy-Hill, and Christopher B Mayhorn. Will the “phisher-men” reel you in?: Assessing individual differences in a phishing detection task. International Journal of Cyber Behavior, Psychology and Learning (IJCBPL), 5(4):1–17, 2015.

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

Ibrahim Alseadoon, Taizan Chan, Ernest Foo, and Juan Gonzalez Nieto. Who is more susceptible to phishing emails?: a saudi arabian study. Association for Information Systems, 2012.

Liu Xiangyu, Li Quyang, and Sonali Chandel. Social engineering and insider threats. In 2017 International Conference on Cyber-Enabled Distributed Computing and Knowledge Discovery (CyberC), pages 25–34. IEEE, 2017.
Peng Wang Wang, Xiaojing Liao Liao, Yue Qin, and Xiaofeng Wang. 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, 2020.

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

Kendra Cherry. The big five personality dimensions: 5 major factors of personality. About.com Guide, 2012.

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

Tzipora Halevi, Nasir Memon, and Oded Nov. Spear-phishing in the wild: A real-world study of personality, phishing self-efficacy and vulnerability to spear-phishing attacks. Phishing Self-Efficacy and Vulnerability to Spear-Phishing Attacks (January 2, 2015), 2015.

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

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

Diksha Goel and Ankit Kumar Jain. Mobile phishing attacks and defence mechanisms: State of art and open research challenges. Computers & Security, 73:519–544, 2018.

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

Ryan T Wright, Matthew L Jensen, Jason Bennett Thatcher, Michael Dinger, and Kent Marett. Research note—Influence techniques in phishing attacks: an examination of vulnerability and resistance. Information Systems Research, 25(2):385–400, 2014.

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

Luca Allodi, Tzouliano Chotza, Ekaterina Panina, and Nicola Zannone. The need for new antiphishing measures against spear-phishing attacks. IEEE Security & Privacy, 18(2):23–34, 2019.

Marianne Junger, Victoria Wang, and Marleen Schlömer. Fraud against businesses both online and offline: crime scripts, business characteristics, efforts, and benefits. Crime Science, 9(1):1–15, 2020.
Sanjay Goel, Kevin Williams, and Ersin Dincelli. Got phished? internet security and human vulnerability. *Journal of the Association for Information Systems*, 18(1):2, 2017.

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

Jacob B. Hirsh, Sonia K. Kang, and Galen V. Bodenhausen. Personalized persuasion: Tailoring persuasive appeals to recipients’ personality traits. *Psychological Science*, 23(6):578–581, 2012. ISSN 0956-7976. doi:10.1177/0956797611436349.

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

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

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

Vaishnavi Bhavsar, Aditya Kadlak, and Shabnam Sharma. Study on phishing attacks. *Int. J. Comput. Appl*, 182:27–29, 2018.

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

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

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

Judith Meinert, Milad Mirbabaie, Sebastian Dungs, and Ahmet Aker. Is it really fake?–towards an understanding of fake news in social media communication. In *International Conference on Social Computing and Social Media*, pages 484–497. Springer, 2018.

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

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

Zuoguang Wang, Hongsong Zhu, and Limin Sun. Social engineering in cybersecurity: Effect mechanisms, human vulnerabilities and attack methods. *IEEE Access*, 9:11895–11910, 2021.

Marius Steffens, Christian Rossow, Martin Johns, and Ben Stock. Don’t trust the locals: Investigating the prevalence of persistent client-side cross-site scripting in the wild. In *NDSS Network and Distributed System Security Symposium*, 2019.

Fumihiro Kanei, Daiki Chiba, Kunio Hato, Katsunori Yoshioka, Tsutomu Matsumoto, and Mitsuaki Akiyama. Detecting and understanding online advertising fraud in the wild. *IEICE Transactions on Information and Systems*, 9:11895–11910, 2021.

Kevin Pfaff, Philipp Ulsamer, and Nicholas H Müller. Where the user does look when reading phishing mails–an eye-tracking study. In *International Conference on Human-Computer Interaction*, pages 277–287. Springer, 2019.
Ryan Heartfield and George Loukas. Detecting semantic social engineering attacks with the weakest link: Implementation and empirical evaluation of a human-as-a-security-sensor framework. *Computers & Security*, 76:101–127, 2018.

Li Xu, Zhenxin Zhan, Shouhuai Xu, and Keying Ye. Cross-layer detection of malicious websites. In *CODASPY*, pages 141–152, 2013.

Sahar Abdelnabi, Katharina Krombholz, and Mario Fritz. Visualphishnet: Zero-day phishing website detection by visual similarity. In *Proceedings of the 2020 ACM SIGSAC Conference on Computer and Communications Security*, pages 1681–1698, 2020.

Yun Lin, Ruofan Liu, Dinil Mon Divakaran, Jun Yang Ng, Qing Zhou Chan, Yiwen Lu, Yuxuan Si, Fan Zhang, and Jin Song Dong. Phishpedia: A hybrid deep learning based approach to visually identifying phishing webpages. *Usenix*, 2021.

Joey Allen, Zheng Yang, Matthew Landen, Raghav Bhat, Harsh Grover, Andrew Chang, Yang Ji, Roberto Perdisci, and Wenke Lee. Mnemosyne: An effective and efficient postmortem watering hole attack investigation system. In *Proceedings of the 2020 ACM SIGSAC Conference on Computer and Communications Security*, pages 787–802, 2020.

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

Akihito Nakamura and Fuma Dobashit. Proactive phishing sites detection. In *2019 IEEE/WIC/ACM International Conference on Web Intelligence (WI)*, pages 443–448. IEEE, 2019.

Saba Eskandarian, Jonathan Cogan, Sawyer Birnbaum, Peh Chang Wei Brandon, Dillon Franke, Forest Fraser, Gaspar Garcia, Eric Gong, Hung T Nguyen, Taresh K Sethi, et al. Fidelius: Protecting user secrets from compromised browsers. In *2019 IEEE Symposium on Security and Privacy (SP)*, pages 264–280. IEEE, 2019.

Enis Ulqinaku, Hala Assal, Abdelrahman Abdou, Sonia Chiasson, and Srdjan Capkun. Is real-time phishing eliminated with fido? social engineering downgrade attacks against fido protocols. *IACR Cryptol. ePrint Arch.*, 2020:1298, 2020.

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

Ludger Goike, Alejandro Quintanar, Kristian Beckers, and Sebastian Pape. Protect—an easy configurable serious game to train employees against social engineering attacks. In *Computer Security*, pages 156–171. Springer, 2019.

Teng Xu, Gerard Goossen, Huseyin Kerem Cevahir, Sara Khodeir, Yingyehze Jin, Frank Li, Shawn Shan, Sagar Patel, David Freeman, and Paul Pearce. Deep entity classification: Abusive account detection for online social networks. In *30th {USENIX} Security Symposium ({USENIX} Security 21)*, 2021.

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

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

Adele E. Howe, Indrajit Ray, Mark Roberts, Malgorzata Urbanska, and Zinta Byrne. The psychology of security for the home computer user. In *Proceedings of the 2012 IEEE Symposium on Security and Privacy, SP ’12*, pages 209–223. Washington, DC, USA, 2012. IEEE Computer Society. ISBN 978-0-7695-4681-0. doi:[10.1109/SP.2012.23](http://dx.doi.org/10.1109/SP.2012.23) URL [http://dx.doi.org/10.1109/SP.2012.23](http://dx.doi.org/10.1109/SP.2012.23)

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

Ponnurangam Kumaraguru, Alessandro Acquisti, and Lorrie Faith Cranor. 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*, page 11. ACM, 2006.

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

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

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