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Toward an Integrated RAT-STT Framework for Understanding Cybercrime in the Age of AI

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Artificial intelligence (AI) is transforming digital environments in ways that fundamentally alter the conditions under which cybercrime emerges. While existing scholarship has documented technological changes in offending techniques, less attention has been paid to how AI reshapes crime opportunity itself. This article addresses that gap by developing an integrated analytical framework combining Routine Activity Theory (RAT) and Space Transition Theory (STT) to explain how structural opportunity conditions and behavioral dynamics interact in AI-mediated environments. The framework conceptualizes AI not merely as a facilitative tool but as a systemic modulator that simultaneously expands offender capacity, algorithmically constructs target suitability, and reshapes guardianship and behavioral constraints. By synthesizing structural and behavioral perspectives, the study demonstrates that contemporary cybercrime should be understood as the outcome of dynamically reconfigured opportunity systems rather than as isolated technological offenses. The article contributes to criminological theory by clarifying the analytical relationship between technological change and crime causation and by providing a unified conceptual model capable of interpreting diverse forms of digitally mediated offending. This study is theoretical in orientation and does not propose a new crime typology, regulatory framework, or empirical measurement, but instead offers a conceptual foundation for future empirical, comparative, and interdisciplinary research on crime in the age of AI.

Keywords: Artificial Intelligence; Cybercrime; Crime Opportunity; Routine Activity Theory (RAT); Space Transition Theory (STT); Opportunity Structures; Theoretical Framework

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1. Introduction

The digital transformation of contemporary societies has generated unprecedented economic, social, and communicative opportunities, while simultaneously producing complex and rapidly evolving security challenges (Kolade et al., 2024; Saeed et al., 2023). Among these, online scams have emerged as one of the most pervasive and adaptive forms of crime within digital environments (Button & Cross, 2017; Kipngetich, 2025). Historically, such scams relied upon human-centered deception, interpersonal persuasion, and the manipulation of trust through direct or semi-direct interaction (Hancock, 2009; Norris, 2019).

The integration of Artificial Intelligence (hereafter 'AI'), however, has fundamentally altered this landscape. Technologies such as generative language models, conversational agents, deepfakes, and voice synthesis have enabled deception to be automated, personalized, and scaled, transforming scams from episodic interpersonal acts into industrialized, data-driven operations (Bociga & Lord, 2026; Schmitt & Flechais, 2024). In this sense, AI functions not merely as a new criminal tool, but as a structural condition that reshapes how crime opportunities are produced, distributed, and exploited (King et al., 2020; Rohozinski & Spirito, 2026; UNODC, 2025).

Existing scholarship across criminology, sociology, victimology, computer science, and law provides important insights into the evolution of scams and their harms. Early research focused on traditional fraud typologies, while later studies documented how digital connectivity expanded the reach and coordination of deceptive practices (Choo & Tan, 2008; Jahankhani et al., 2014; Koning et al., 2024). Victimological research has further demonstrated that susceptibility to scams is shaped not by individual gullibility, but by the strategic exploitation of trust, authority, urgency, and emotional need (Button et al., 2014; Norris, 2019; Shang et al., 2023; Whitty, 2019). Yet much of this literature remains grounded in human-mediated deception and does not fully account for AI-specific affordances such as synthetic interaction, adaptive persuasion, persistent conversational agents, and algorithmic targeting (Ho et al., 2025; Schmitt & Flechais, 2024; Velutharambath et al., 2025).

Notably, from a criminological perspective, these transformations cannot be adequately understood without attention to how AI restructures the conditions under which crime occurs. Routine Activity Theory (hereafter 'RAT') explains crime as the convergence of motivated offenders, suitable targets, and absence of capable guardianship (Cohen & Felson, 1979; Leukfeldt & Yar, 2016; Yar, 2005), whereas Space Transition Theory (hereafter 'STT') accounts for behavioral and normative shifts that occur when individuals move between physical and digital environments (Choi, 2025; Jaishankar, 2008; Zhou et al., 2024). Each framework captures important but partial dimensions of contemporary cybercrime. RAT in principle clarifies structural opportunity dynamics but under-specifies behavioral transformation (Felson & Clarke, 1998; Kigerl, 2012; Reyns, 2017; Vakhitova et al., 2015), while STT explains behavioral adaptation but remains less precise regarding technological restructuring of opportunity conditions (Al Shamsi et al., 2023; Assarut et al., 2019; Jaishankar, 2019).

The rise of AI renders this theoretical separation increasingly untenable. AI simultaneously expands offender capacity, algorithmically constructs target suitability, strains guardianship mechanisms, and intensifies identity fluidity and dissociative anonymity across digital spaces (Dobusch & Schoeneborn, 2015; Graham & Triplett, 2017; Weulen Kranenbarg et al., 2021). Understanding contemporary cybercrime thus requires a framework capable of explaining both structural opportunity transformation and behavioral transition within technologically mediated environments (Vakhitova, 2025; Završnik, 2021).

Against this backdrop, this study addresses the central question of how AI reconfigures crime opportunities and what this transformation implies for victimization and justice. Building upon prior work applying STT to digital offender profiling (Choi, 2025), this research integrates STT with RAT (Choi et al., 2025) into a unified analytical framework. This integrated RAT-STT model provides a dual-lens approach that simultaneously accounts for structural constraints and the process of behavioral transformations. Consequently, the analysis demonstrates how AI reshapes scam mechanisms, generates new victimization patterns, and exposes limitations in existing legal and institutional responses.

Accordingly, this article does not seek to introduce a new crime typology, nor does it aim to offer a regulatory analysis or provide empirical measurements of cybercrime trends. Instead, the study's primary contribution is theoretical: it develops an integrated RAT-STT framework that explains how AI reconfigures the mechanics of cybercrime opportunity and behavioral adaptation. By conceptualizing AI as a structural condition that simultaneously transforms opportunity structures and behavioral dynamics, the article offers a unified analytical lens for understanding cybercrime beyond offense-specific or technology-centered accounts.

2. Theoretical Foundations of Crime Opportunity in AI-Mediated Environments

Understanding cybercrime in the age of AI requires theoretical frameworks capable of explaining not only how crime is committed but how the conditions that make crime possible are structurally produced and dynamically transformed (Adewopo et al., 2025; Berk, 2021; Lavorgna & Ugwudike, 2021). In digitally mediated environments, opportunity is no longer a static situational configuration but an adaptive and technologically modulated system shaped by automation, data infrastructures, and algorithmic interaction (Brayne & Christin, 2021; Peeters & Schuilenburg, 2018). Conventional criminological approaches that treat crime as the outcome of individual motivation or deviant disposition are therefore insufficient for explaining contemporary AI-mediated offenses, which emerge within socio-technical environments that systematically organize exposure, vulnerability, and behavioral interaction (Opp, 2020; Sullivan, 2022; Wikstrom & Kroneberg, 2022).

Among existing criminological theories, RAT and STT, in particular, provide valuable analytical foundations because they examine complementary dimensions of crime causation. RAT conceptualizes crime as the product of structural convergence among motivated offenders, suitable targets, and

absent or ineffective guardianship (Brantingham & Brantingham, 2016; Felson, 2016; Hollis-Peel et al., 2011). Its core contribution hence lies in shifting explanatory emphasis away from offender pathology toward opportunity structure, demonstrating that crime rates fluctuate when environmental conditions alter the likelihood of such convergence (Clarke, 1995; Hipp, 2016; Kleemans et al., 2012; Schaefer & Mazerolle, 2017).

In contrast, STT elucidates the erosion of behavioral norms as individuals transition from physical to digital spaces. It posits that the interplay of anonymity, identity fluidity, and diminished social deterrence fundamentally alters moral constraints, thereby lowering the threshold for deviant conduct (Capurro et al., 2013; Jaishankar, 2010, 2018; Wen & Miura, 2025). While prior research has explored behavioral dynamics of digital offending through STT (Choi, 2025), the present study extends this approach by incorporating structural opportunity conditions through RAT (Choi et al., 2025), thereby developing an integrated explanatory framework. Collectively, these theories encompass both the structural and behavioral conditions shaping cybercrime. However, their divergent analytical emphases suggest the necessity for an integrated perspective that bridges opportunity structures with behavioral dynamics in technologically mediated environments.

1) Routine Activity Theory (RAT) and Opportunity as Structural Condition

RAT provides a foundational framework for analyzing technologically mediated crime because it treats criminal events as contingent upon situational configurations rather than individual predispositions (Cohen & Felson, 1979; Leukfeldt & Yar, 2005). In digital environments, these configurations are profoundly reshaped by AI. Continuous connectivity, platform integration, and automated communication expand target accessibility, while scalable digital infrastructures reduce offender effort and perceived risk (King et al., 2020; Lavorgna, 2014; Wall, 2024). As a result, the convergence of offenders, targets, and guardianship described by RAT becomes more frequent, more distributed, and less temporally constrained (Miller, 2013; Soudijn & Zegers, 2012; Vakhitova, 2025).

AI amplifies each element of the RAT triad. First of all, it lowers barriers to entry for offenders by providing user-friendly tools capable of generating persuasive content, impersonating identities, and automating interaction (Faqir, 2023; Hayward & Maas, 2020). Second, it transforms target suitability by enabling predictive profiling, allowing offenders to identify and tailor approaches to individuals based on behavioral data, social signals, and contextual cues (Brand, 2020; Huseynov & Ozdenizci Kose, 2022; Završnik, 2021). Third, it strains guardianship capacity by overwhelming detection systems with adaptive and rapidly generated content (Bossler & Holt, 2009; Ekundayo et al., 2024; Williams, 2016). As established in the theoretical integration section, AI accelerates opportunity convergence by reducing operational barriers, facilitating mass personalization, and outpacing traditional guardianship through its inherent speed and scale.

In this sense, AI does not merely assist or facilitate criminal conduct; it reconfigures the very landscape of criminal opportunity. Crime thereby is becoming

less dependent on physical proximity or prolonged effort, relying instead on automated, algorithmic coordination and digital vulnerability patterns (Homeland Security, 2024; Spyropoulos, 2024; UNODC, 2025; Wisnubroto & Tegnan, 2025). Opportunity is thus transformed from a localized situational condition into a distributed system characteristic of routine participation in digital life (Brenner, 2002; Romagna & Leukfeldt, 2024).

2) Space Transition Theory (STT) and Behavioral Dynamics in Digital Environments

Where RAT explains how opportunity structures emerge, STT demonstrates how individuals behave within them. STT posits that transitions between physical and virtual environments produce shifts in identity, moral restraint, and normative expectations. Digital environments—characterized by anonymity, dissociation (dissociative distance), and reduced deterrence—facilitate behaviors that are unlikely in offline settings (Chen et al., 2025; Cohen, 2007; Jaishankar, 2008, 2010). These shifts occur not because individuals become inherently deviant, but because environmental conditions alter perceptions of accountability, risk, and social feedback (Apene et al., 2024; Lapidot-Lefler & Barak, 2012).

AI intensifies these dynamics by introducing synthetic interaction, automated agents, and identity simulation into online environments. These features expand identity fluidity and create psychological distance between actors and consequences (Adler et al., 2024; Igba et al., 2025). Offenders may interact through avatars, generated personas, or bots, reducing emotional salience and moral inhibition. At the same time, AI systems can simulate empathy, memory, and conversational continuity, increasing victims' emotional engagement and compliance (Rosenberg, 2023; Rostami & Navabinejad, 2023). This results in a dangerous asymmetry: offenders remain detached while victims become deeply immersed in a fabricated relationship.

STT thus clarifies how technological mediation alters not only the structure of opportunity but also the psychological conditions under which deception becomes possible (Burrell, 2025; Ho et al., 2025; Velutharambath et al., 2025). As described in the discussion of identity and anonymity dynamics, digital environments enable individuals to maintain multiple synthetic identities and to shift between them rapidly, thereby distancing action from accountability (Arslan, 2023; Schmitt & Flechais, 2024). These processes demonstrate that cybercrime cannot be fully understood without accounting for the behavioral transformations associated with movement across digitally mediated spaces.

3) Limits of Single-Theory Explanations

Although both RAT and STT offer powerful insights, each theory is analytically incomplete when applied in isolation. RAT excels at explaining how opportunity structures expand or contract but does not fully specify how digital environments transform motivation, identity, or moral constraint (Vakhitova, 2025; Vakhitova et al., 2015; Willison & Backhouse, 2006). On the other hand, STT illustrates behavioral adaptation, but it offers limited insight into how technological infrastructures systematically create and

distribute criminal opportunities (Assarut et al., 2019; Choi, 2025; Salleh & Selamat, 2022). When used independently, each theory captures only part of the explanatory landscape.

This limitation becomes especially pronounced in AI-mediated contexts, where structural and behavioral transformations occur simultaneously. AI alters opportunity conditions through automation, scalability, and predictive targeting, while also reshaping behavioral dynamics through anonymity, simulation, and algorithmic interaction (Mokoena et al., 2023; Spyropoulos, 2024; Wall, 2024). Analytical approaches prioritizing exclusively structural or behavioral explanations fail to capture the reciprocal interaction between environment and action, which is fundamental to contemporary cybercrime (Hipp, 2010; Wikstrom & Kroneberg, 2022).

4) Toward a Unified Theoretical Perspective

The convergence of these insights points toward the necessity of theoretical integration (Kavish & Boutwell, 2018; Opp, 2020). AI functions as a systemic modulator that simultaneously reshapes opportunity structures and behavioral conditions (Schmitt & Flechais, 2024; Wisnubroto & Tegnan, 2025). By lowering effort thresholds, expanding target reach, and weakening guardianship, it reorganizes the structural conditions identified by RAT (Haley & Burrell, 2025; Reyns et al., 2011). By enabling identity fluidity, dissociative interaction, and norm displacement, it intensifies the behavioral mechanisms described by STT (Choi, 2025; Van der Wagen & Pieters, 2015). The explanatory power of each theory is therefore strengthened when considered together rather than separately.

This integrated perspective reframes AI-mediated crime as a phenomenon arising from dynamically reconfigured opportunity systems rather than isolated acts of deception (Bociga & Lord, 2026; Fiorinelli & Zucca, 2025). Crime becomes intelligible as the product of feedback processes linking technological infrastructure, human behavior, and institutional control (Aebi et al., 2025; Lewis & Lewis, 2011; Yeboah-Ofori & Opoku-Boateng, 2023). Such a perspective also clarifies why contemporary cybercrime is increasingly scalable, adaptive, and resistant to traditional forms of regulation: the conditions that enable it are embedded within routine digital interaction rather than confined to exceptional or abnormal situations (Dupont & Whelan, 2021; Katyal, 2002; Kipngetich, 2025).

5) Analytical Implications for the Present Study

Building on this theoretical foundation, the present study adopts an integrated RAT-STT approach to analyze how AI reconfigures crime opportunity in digitally mediated environments. This integrated model merges structural and behavioral dimensions, and provides a unified framework for analyzing the intricate dynamics of contemporary cybercrime (Ahmad & Thurasamy, 2022; Leukfeldt & Yar, 2016; Martineau et al., 2023). The sections that follow apply this framework to three related questions: (1) how AI generates new mechanisms of offending (Caldwell et al., 2020; Faqir, 2023; King et al., 2020), (2) how reconfigured opportunities produce observable outcomes (Lazarus et al., 2025; Porcedda

& Wall, 2019), and (3) what implications these transformations hold for legal, institutional, and policy responses (Goldsmith & Brewer, 2014; Kuziemski & Misuraca, 2020; Salehi et al., 2025). Importantly, this study does not propose a new standalone theory but develops an integrated explanatory framework in which structural opportunity and behavioral transition are analytically interdependent and jointly shape cybercrime in AI-mediated environments.

3. An Integrated RAT - STT Framework

The preceding discussion demonstrates that neither structural opportunity approach (RAT) nor behavioral transition model (STT) alone can adequately explain cybercrime in environments shaped by AI. Contemporary digital offending emerges from the simultaneous interaction of technologically produced opportunity structures and psychologically mediated behavioral dynamics (Akinbowale et al., 2025; Hughes & Hutchings, 2023). Building on the theoretical foundations, this section develops an integrated analytical framework that combines RAT and STT. Instead of treating the two theories as parallel or independent, the proposed framework conceptualizes them as analytically interdependent, linking structural opportunity conditions to behavioral transition dynamics within AI-mediated environments.

The framework is intended not as a standalone predictive model, but as a conceptual and analytical structure for understanding how cybercrime opportunity is reconfigured through the interaction of structural and behavioral processes. By positioning AI as a mediating condition that simultaneously reshapes opportunity structures and behavioral patterns, it provides a coherent basis for interpreting contemporary cybercrime beyond single-theory or offense-specific approaches. The analytical task, therefore, is not to choose between RAT and STT, but to integrate them into a unified framework that captures the reciprocal relationship between environmental conditions and human action in contemporary AI-mediated contexts.

1) Conceptual Logic of Integration

Notably, RAT and STT address different but interdependent explanatory domains. RAT specifies the structural conditions that make crime possible, emphasizing convergence among offenders, targets, and guardianship (Groff, 2007; Wortley & Townsley, 2016). In contrast, STT specifies the behavioral transformations that make crime more likely, emphasizing shifts in identity, norm perception, and deterrence across environments (Al Shamsi et al., 2023; Shetty et al., 2024). The theoretical limitation of treating these frameworks separately lies in the implicit assumption that opportunity structures and behavioral dynamics operate independently. In digitally mediated environments, however, they are mutually constitutive (Chiao, 2019; Fleetwood, 2016).

AI collapses the analytical boundary between these domains. Structural conditions increasingly shape behavior in real time through algorithmic interaction (Brand, 2020; Karunamurthy et al., 2023; Wilcox et al., 2018), while behavioral responses simultaneously reconfigure opportunity structures through data generation, adaptive targeting, and recursive feedback loops (Adanyin, 2024; Bello, 2025; Jabir

et al., 2025). Opportunity and behavior thus form a recursive system rather than sequential stages (Granic & Patterson, 2006; Mead & Neves, 2018). A theoretical model capable of explaining AI-mediated crime must therefore conceptualize structure and behavior as dynamically linked components of a single analytical architecture.

2) AI as Structural–Behavioral Modulator

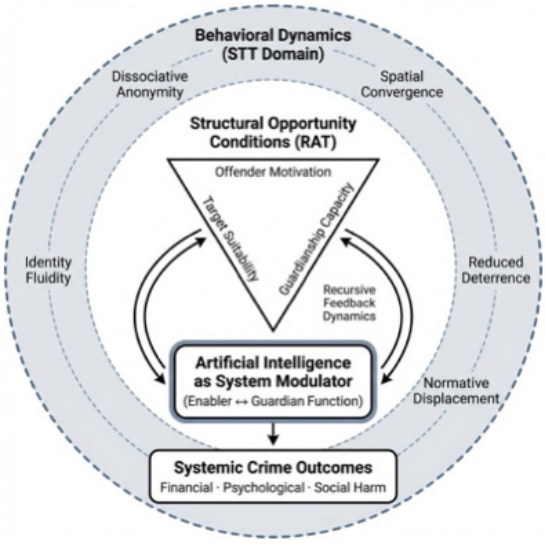
Within the integrated framework proposed here, AI is conceptualized not as an external tool used by offenders but as a central modulating condition that influences all components of the crime environment simultaneously (Caianiello, 2019; Smith, 2026). AI expands offender capacity by lowering technical barriers, automating engagement, and enabling deception at scale (Aebi et al., 2025; Bello, 2025; Pawar et al., 2021). It affects target suitability by transforming individuals into continuously profiled and algorithmically interpretable subjects (Al Fahdi et al., 2016; Büchi et al., 2023). In addition, AI influences guardianship by straining detection systems, complicating attribution, and generating adaptive adversarial behavior (Malatji & Tolah, 2025; Sudhakaran & Kshetri, 2026). At the same time, AI is reshaping behavioral conditions by enabling synthetic identities, persistent interaction, and emotional simulation, thereby altering human perceptions of risk, accountability, and authenticity (Pakina et al., 2023; Sharma et al., 2025).

This dual influence means that AI operates as both an environmental force and a behavioral catalyst. It thus reorganizes situational convergence while simultaneously modifying how actors perceive, interpret, and respond to that convergence (Ayling, 2011; Ekblom, 2017; Schiliro, 2024). In this sense, AI functions as a structural-behavioral bridge linking the explanatory domains of RAT and STT. The significance of this role is analytical rather than technological: it provides a conceptual mechanism through which structural and behavioral processes can be understood as co-evolving rather than independent.

As illustrated in <Figure 1>, the framework is organized as a layered analytical system. The inner RAT layer represents structural opportunity conditions defined by the convergence of offenders, targets, and guardianship, while the surrounding STT layer captures behavioral transformations associated with digitally mediated environments, including anonymity, identity fluidity, and norm conflict. AI hence is positioned beneath these layers as a systemic modulator, reflecting its role in simultaneously reshaping opportunity structures and behavioral conditions rather than operating as an independent causal factor. The bi-directional arrows indicate recursive feedback dynamics through which technological affordances, human behavior, and institutional constraints co-evolve. The resulting configuration demonstrates that AI-enabled online scams are best understood not as isolated deceptive acts but as emergent outcomes of dynamically reconfigured opportunity environments.

3) Opportunity Reconfiguration Mechanisms

Integrating RAT and STT highlights that AI-mediated crime represents a reconfiguration of opportunity rather than a mere expansion. This distinction is critical to better understand the evolving nature of digital offenses (Allah Rakha, 2024; Rossy & Ribaux, 2020;



<Figure 1> Conceptual Architecture of the Integrated RAT-STT Framework for AI-Mediated Cybercrime[1)]

Willison & Backhouse, 2006). Importantly, AI alters the spatial, temporal, relational, and informational dimensions of crime opportunity simultaneously (Butt et al., 2021; King et al., 2020; Zhou et al., 2024).

Spatially, digital environments erase physical borders, enabling offenders and targets to collide across global jurisdictions (Arnell & Faturoti, 2023; Lazarus, 2025; Mokoena et al., 2023). Temporally, automated systems allow continuous interaction, eliminating traditional limits on duration and/or frequency of contact (Bello, 2025; Van der Wagen & Pieters, 2015). Relationally, synthetic personas and simulated communication fundamentally reconfigures the landscape of interpersonal dynamics, facilitating deception to occur within seemingly authentic relationships (Čekić, 2024; George et al., 2023). Informationally, the convergence of predictive analytics and data aggregation transform inherent behavioral uncertainty

1) <Figure 1> illustrates the integrated RAT-STT framework, mapping how structural opportunities and behavioral dynamics converge within AI-mediated environments to drive modern cybercrime. This analytical framework was independently developed [and proposed] by the Author, drawing upon and synthesizing interdisciplinary scholarship on routine activity theory, space transition theory, situational action theory, AI-mediated crime environments, and cybercrime guardianship dynamics, including, inter alia [in alphabetical order]: Apene et al. (2025); Brewer et al. (2019); Caldwell et al. (2020); Chiao (2019); Choi (2025); Choi et al. (2025); Clarke (1995); Cohen & Felson (1979); Ekblom (2017); Faqir (2023); Felson (2016); Goldsmith & Brewer (2015); Holt & Bossler (2016); Jaishankar (2008, 2019); King et al. (2020); Leukfeldt & Yar (2016); Martineau et al. (2023); Reyns (2017); Schaefer & Mazerolle (2017); Vakhitova (2025); Vakhitova et al. (2015); Wall (2024); Wikstrom & Kroneberg (2022); Wilcox et al. (2018); Wortley & Townsley (2016); Yar (2005); Završnik (2021); Zhou et al. (2024).

into precise probabilistic targeting, thereby optimizing operational efficiency and reinforcing normative compliance (Arslan, 2023; Berk, 2021; Ekundayo et al., 2024).

These transformations indicate that opportunity is no longer a passive situational condition but an actively engineered environment. Digital offenders no longer merely encounter opportunities; they can design, replicate, and scale them (Broadhurst, 2021; Ekblom, 2017; Leukfeldt & Jansen, 2019). The result is a shift from situational opportunism to systemic opportunity production.

4) Feedback Dynamics Between Structure and Behavior

A central contribution of the integrated framework is its capacity to explain feedback dynamics linking structural opportunity and behavioral adaptation. In AI-mediated environments, structural changes alter behavioral incentives, and behavioral responses in turn reshape structural conditions (Groff, 2007; Hipp, 2016). For example, automated targeting increases victim exposure, generating additional data that refine predictive models and further enhance targeting accuracy (Ejjami, 2024; Haley & Burrell, 2025). Similarly, adaptive detection systems modify offender strategies, prompting iterative evasion techniques that reshape guardianship mechanisms (Gilbert et al., 2025; Quibell, 2024).

These recursive interactions give rise to an evolutionary dynamic resembling a co-adaptive system rather than a static environment. Crime opportunity becomes a moving equilibrium shaped by continuous interaction among offenders, targets, guardians, and technological infrastructures (Apene et al., 2024; Kigerl, 2012). This dynamic perspective helps explain why AI-mediated crime often appears resistant to traditional forms of prevention and control: interventions targeting one component of the system may trigger adaptive responses in another (Borgesano et al., 2025; Braithwaite, 2020; Selvadurai, 2025).

5) Analytical Value of the Integrated Model

The theoretical value of the integrated RAT-STT framework lies in its ability to unify previously fragmented explanations of cybercrime. Rather than treating contemporary digital offenses as anomalies requiring entirely new theoretical approach, the framework postulates how established criminological principles can be extended and recombined to account for technological transformation (Holt & Bossler, 2016; Maimon & Louderback, 2019; Opp, 2020; Leukfeldt & Yar, 2016). It therefore preserves the explanatory strengths of both theories while compensating for their respective limitations.

More specifically, the developed model shows that contemporary cybercrime should be understood not simply as technologically facilitated wrongdoing, but as the result of structurally produced opportunities interacting with behaviorally transformed actors (Aebi et al., 2025; Jaishankar, 2008; Smith, 2026). This reconceptualization shifts analytical attention from isolated incidents to systemic environments (Bello, 2025; Farrell & Pease, 2017; Wortley & Townsley, 2016), from individual culpability to situational configurations (Clarke, 1995; Leukfeldt & Jansen, 2019; Wilcox et al., 2018), and from static risk factors to dynamic interaction processes (Maimon

& Browning, 2012; McMillon et al., 2014). Such a perspective is especially useful for analyzing AI-mediated offenses, which are characterized by scalability, persistence, and adaptability.

6) Framework Implications for Subsequent Analysis

The proposed framework (Figure 1) provides the conceptual structure that guides the remainder of this study. It sets out three analytical propositions that organize the sections that follow. First, AI-mediated crime should be understood not as a collection of separate techniques, but as observable expressions of reconfigured opportunity. Second, outcomes such as victimization patterns and institutional strain are best understood as systemic consequences of these conditions. Third, legal and policy responses should be evaluated according to their ability to address both structural opportunity and behavioral dynamics.

These propositions are not empirical claims but analytical premises. Their purpose is to guide interpretation and clarify causal logic. By showing how structural and behavioral factors interact in digitally mediated environments, the framework offers a coherent lens for examining diverse cybercrime phenomena without fragmenting analysis into isolated explanatory models. Drawing upon those propositions, the following section examines the mechanisms of contemporary AI-mediated cybercrime as illustrative manifestations of the integrated framework, thereby demonstrating how reconfigured opportunity conditions are translated into observable patterns of offending.

4. Mechanisms of AI-Mediated Cybercrime

The mechanisms discussed in this section are presented not as discrete categories, but as illustrative manifestations of the integrated RAT-STT framework developed in Section 3. From this perspective, AI-mediated cybercrime is best understood not merely as technologically facilitated offending, but as the outcome of identifiable mechanisms through which reconfigured opportunity conditions are translated into actionable criminal behavior.

These mechanisms operate at the intersection of structural opportunity and behavioral transformation, linking technological affordances to observable patterns of offending (Bossler & Holt, 2009; Caldwell et al., 2020; Reyns, 2017; Wikstrom & Kroneberg, 2022). Rather than treating AI as a tool occasionally employed by offenders, this section conceptualizes it as an enabling infrastructure that systematically reorganizes how opportunities are generated, perceived, and exploited.

1) Automation of Offender Capacity

One of the most consequential mechanisms introduced by AI is the automation of offender activity Traditional forms of deception required sustained human effort, interpersonal skill, and temporal investment (Butt et al., 2021; Treleaven et al., 2023; Yar & Steinmetz, 2023). AI systems reduce these requirements by generating persuasive messages, synthesizing identities, and maintaining continuous interaction without direct human intervention (Bello, 2025; Jahan & Mell, 2024; Malatji & Tolah, 2024). When

less effort is needed, it becomes easier for even non-experts to commit sophisticated digital crimes. (Apene et al., 2024; Holt & Bossler, 2016; Leukfeldt et al., 2017). The resulting expansion of offender capacity does not merely increase crime volume; it alters the structural relationship between effort and reward, making cybercrime more scalable, persistent, and economically efficient (Bossler & Holt, 2009; Maimon & Louderback, 2019; Wall, 2024).

From a RAT perspective, automation increases the likelihood of offender-target convergence by enabling simultaneous engagement with multiple targets (Leukfeldt & Yar, 2016; Reyns, 2017). From an STT perspective, automation distances actors from the psychological consequences of their actions, reducing moral inhibition and facilitating norm displacement (Jaishankar, 2008; Williams, 2016; Zhuo et al., 2024). The same technological feature therefore operates simultaneously as a structural amplifier and a behavioral catalyst (Ekblom, 2017; Goldsmith & Brewer, 2015).

2) Algorithmic Construction of Target Suitability

AI also transforms the notion of target suitability (Büchi et al., 2023; Ekundayo et al., 2024). In traditional opportunity theory, suitable targets are those whose characteristics make victimization feasible or attractive (Cohen & Felson, 1979; Felson & Clarke, 1998; Miller, 2013). By contrast, in contemporary AI-mediated environments, target suitability is no longer passively encountered but actively constructed through algorithmic analysis (Al Fahdi et al., 2016; De Hert & Lammerant, 2016; Dzuba, 2025). Behavioral data, interaction patterns, and platform metadata allow digital offenders—or automated systems acting on their behalf—to identify individuals most likely to respond to specific forms of manipulation (Butkovic et al., 2018; Pakina et al., 2023; Schiliro, 2024).

This predictive targeting shifts the logic of crime from chance encounters to intentional selection. Offenders can now target individuals whose digital profiles indicate vulnerability, receptivity, or contextual susceptibility (Benbouzid, 2019; Ward & Durrant, 2011; Whitty, 2019). Such processes reduce uncertainty and increase efficiency, reinforcing the structural convergence conditions described by RAT (Pratt et al., 2010; Reyns, 2017; Williams, 2016). At the same time, personalized interaction enhances relational credibility and emotional immersion, intensifying the behavioral mechanisms identified by STT (Button et al., 2014; Suler, 2004; Buchanan & Whitty, 2014). Target suitability thus becomes a dynamic variable shaped through continuous data interpretation rather than a static attribute of individuals (Andrejevic & Gates, 2014; Zuboff, 2019).

3) Synthetic Identity and Interaction Simulation

A further mechanism linking structural and behavioral dynamics is the capacity of AI systems to generate synthetic identities and simulate interaction (Chesney & Citron, 2019; Jahan & Mell, 2024). Digital personas can be constructed rapidly, modified continuously, and deployed across multiple platforms, allowing offenders to operate through layers of mediated representation (Capurro et al., 2013;

Hancock & Bailenson, 2021; Paris, 2021). These synthetic identities facilitate deception not only by obscuring attribution but by producing the appearance of authenticity, familiarity, or authority (Alder et al., 2024; Tolosana et al., 2020).

From a structural standpoint, identity simulation reduces the risks associated with exposure, thereby weakening guardianship effectiveness (Caldwell et al., 2020; Karnouskos, 2020). From a behavioral standpoint, simulated interaction reshapes social perception, enabling targets to interpret automated communication as genuine interpersonal engagement (Cheng, 2023; Rashid et al., 2025). Emotional cues, conversational continuity, and contextual adaptation can create the impression of a stable relational partner, increasing trust and compliance (McKay & Macintosh, 2024; Rosenberg, 2023; Whitty, 2019). This mechanism demonstrates how technological affordances concurrently alter situational opportunity and cognitive interpretation, thereby reinforcing the analytical necessity of integrating RAT and STT (Choi, 2025; Choi et al., 2025; Ekblom, 2017; Goldsmith & Brewer, 2015; Jaishankar, 2008).

4) Temporal Persistence and Interaction Continuity

AI also introduces a temporal dimension that distinguishes contemporary cybercrime from earlier forms of digital deception (Allah Rakha, 2024; Čekić, 2024). Automated agents can maintain continuous interaction across extended periods, eliminating the temporal constraints that traditionally limited offender activity (Bello, 2025; Hughes & Hutchings, 2023). Persistence increases exposure probability, allowing repeated engagement attempts and adaptive message refinement based on recipient response patterns (Buchanan & Whitty, 2014; Rohozinski & Spirito, 2026).

This persistence affects both opportunity structure and behavioral response (Cohen & Felson, 1979; Granic & Patterson, 2006; Wikstrom & Kroneberg, 2022). Structurally, extended interaction duration increases the likelihood of convergence between offender and target (Ilievski, 2016; Reyns et al., 2011; Yar & Steinmetz, 2023). Behaviorally, repeated communication fosters familiarity and reduces skepticism, gradually normalizing interaction that might initially appear suspicious (Michael & Brewer, 2025; Vakhitova, 2025) Over time, targets may reinterpret the interaction as routine rather than exceptional, a shift that lowers psychological resistance (Modic & Anderson, 2015; Stajano & Wilson, 2011). Temporal continuity thus operates as a mechanism through which digital environments reshape perception and decision-making processes.

5) Distributed and Scalable Opportunity Production

Perhaps the most significant transformation introduced by AI-mediated environments is the shift from opportunistic offending to systemic opportunity production (Brayne & Christin, 2021; King et al., 2020). In physical settings, opportunities arise sporadically and are constrained by proximity, timing, and effort (Felson & Clarke, 1998; Wortley & Townsley, 2016). In AI-mediated environments, opportunities can be designed, replicated, and distributed across networks at scale (Apene et al., 2024;

Kipngetich, 2025). Automated scripts, adaptive algorithms, and platform infrastructures enable offenders to generate large numbers of interaction scenarios simultaneously (Broadhurst, 2021; Haley & Burrell, 2025; Huseynov & Ozdenizci Kose, 2022).

As Felson observed in his 2016 work, such capacity fundamentally transforms the ontology of opportunity itself. Opportunity is no longer a situational condition awaiting discovery; it becomes an engineered resource subject to optimization (Faqir, 2023; Felson, 2016; Maimon & Louderback, 2019; Wisnubroto & Tegnan, 2025). Structural convergence is therefore no longer contingent on chance but can be strategically orchestrated. As a result, the distinction between opportunity and strategy collapses, producing a system in which criminal activity resembles a coordinated process rather than isolated events (Leukfeldt et al., 2017; Lavorgna, 2014; Schiliro, 2024).

6) Adaptive Feedback and Evolutionary Dynamics

The mechanisms described above do not operate independently. They interact through feedback processes that produce adaptive system behavior. Automated targeting generates data; these data refine predictive models, and refined models further enhance targeting accuracy (Ekundayo et al., 2024; Granic & Patterson, 2006; Haley & Burrell, 2025). Meanwhile, detection efforts provoke evasion strategies, which in turn reshape detection systems. Together, this resulting dynamic constitutes a co-evolutionary environment characterized by continual adjustment among offenders, targets, guardians, and technological infrastructures (Cable et al., 2024; Do & Selvadurai, 2025).

These feedback dynamics help explain why AI-mediated cybercrime often appears resilient to traditional prevention approaches. Interventions that target one mechanism may trigger adaptive responses in another, thereby sustaining the overall system equilibrium (Apene et al., 2024; Braithwaite, 2020; Hayward & Maas, 2021; Van Elteren et al., 2024). Understanding cybercrime as a dynamic system rather than a static phenomenon therefore becomes essential for accurate analysis (Opp, 2020; Smith, 2026; Wikstrom & Kroneberg, 2022). The integrated RAT-STT framework provides the conceptual tools necessary to interpret these processes because it captures both the structural conditions enabling adaptation and the behavioral processes through which adaptation occurs (Cullen et al., 2008; Dzuba, 2025; Goldsmith & Brewer, 2014; Ilievski, 2016).

Taken together, the mechanisms identified in this section demonstrate how AI translates reconfigured opportunity conditions into operational forms of cybercrime. The next section then examines the observable consequences of these processes, showing how systemic opportunity transformation manifests in patterns of harm, victimization, and institutional strain.

5. Outcomes of Reconfigured Opportunity

As the preceding analysis shows, AI not only expands cybercrime opportunities but fundamentally reconfigures the conditions that produce them (Caldwell et al., 2020; King et al., 2020). If the

integrated RAT-STT framework is analytically robust, these transformations should generate observable effects (consequences) extending beyond individual incidents of offending (Farrell & Pease, 2017; Leukfeldt & Yar, 2016; Quibell, 2024; Spyropoulos, 2024). Such consequences are not incidental by-products of technological misuse; they are structural outcomes generated by the interaction between altered opportunity environments and behaviorally transformed actors (Leukfeldt et al., 2017; Maimon & Louderback, 2019). This section therefore analyzes the structural implications of those reconfigured opportunity conditions as they become visible in observable distributions of injury, exposure, and institutional pressure.

1) Victimization as a Structural Outcome

In traditional criminological analysis, victimization is often treated as a contingent outcome resulting from individual exposure or misfortune (Finkelhor & Asdigian, 1996; Schreck et al., 2002; Vakhitova et al., 2015). Under AI-mediated conditions, however, victimization increasingly reflects the systemic properties of digital environments rather than isolated situational encounters (Büchi et al., 2023; Ilievski, 2016; Reyns, 2017; Smith, 2026). Automated targeting, predictive profiling, and persistent interaction mechanisms reshape the distribution of risk across populations, producing patterns of exposure that are structured rather than random (Benbouzid, 2019; De Hert & Lammerant, 2016; Modic & Anderson, 2014; Whitty, 2019).

Interpreted within the RAT framework, these developments intensify the convergence of offenders and suitable targets while simultaneously weakening guardianship capacity (Cohen & Felson, 1979; Pratt et al., 2010; Yar, 2005). AI increases the likelihood of such convergence not only by expanding offender reach but by continuously recalculating target suitability through data analysis (Butkovic et al., 2018; Ekundayo et al., 2024; Pakina et al., 2023). From the perspective of STT, the same conditions reshape behavioral responses, reducing skepticism, increasing compliance, and fostering emotional engagement (Choi, 2025; Jaishankar, 2008; Suler, 2004). Victimization thus emerges as a systemic effect of interacting structural and behavioral processes rather than a function of individual vulnerability alone (Holt & Bossler, 2016; Leukfeldt & Yar, 2016; Van Wilsem, 2011).

2) Expansion and Differentiation of Harm

The reconfiguration of opportunity conditions also alters the nature and distribution of harm (Button & Cross, 2017; Whitty, 2019). AI-mediated offenses frequently produce multidimensional consequences that extend beyond immediate financial loss (Ho et al., 2025; Modic & Anderson, 2015). Psychological distress, reputational damage, relational disruption, and prolonged uncertainty may accompany or even exceed material harms (Buchanan & Whitty, 2014; Gilbert et al., 2025; Kipngetich, 2025). These effects arise in part because technologically mediated interactions blur boundaries between authentic and simulated communication, complicating individuals' ability to assess credibility and intent (Assarut et al., 2019; Sudhakaran & Kshetri, 2026).

More importantly, the scale and persistence of

AI-enabled interactions can amplify these harms. Automated systems may maintain contact over extended periods, increasing emotional investment and deepening perceived relational ties (Button et al., 2014; Pawar et al., 2021; Whitty, 2019). When deception is later revealed, the resulting sense of betrayal or manipulation may be experienced as personally directed rather than structurally produced (Akinbowale et al., 2025; Stajano & Wilson, 2011; Buchanan & Whitty, 2014). This phenomenon illustrates how behavioral mechanisms identified by STT interact with opportunity structures identified by RAT to produce consequences that are both materially and psychologically significant (Ahmad & Thurasamy, 2022; Choi, 2025b; Goldsmith & Brewer, 2014; Jaishankar, 2008; Leukfeldt & Yar, 2016).

3) Redistribution of Risk and Exposure

Another consequence of reconfigured opportunity environments is the redistribution of victimization risk across demographic, social, and situational contexts. Rather than selecting targets at random, AI-enabled systems can identify and prioritize specific user categories based on behavioral indicators, platform activity, or contextual signals (Büchi et al., 2023; De Hert & Lammerant, 2016; Jahan & Mell, 2024). As a result, exposure to cybercrime may become patterned according to algorithmically inferred characteristics rather than traditional criminogenic factors such as geographic proximity or routine physical activities (Benbouzid, 2019; Butkovic et al., 2018; Hayward & Maas, 2020).

This redistribution does not necessarily imply that certain groups are inherently more vulnerable. Instead, it reflects the logic of predictive targeting, in which algorithmic processes generate probabilistic assessments of responsiveness (Arslan, 2023; Berk, 2021; Finkelhor & Asdigian, 1996; Schreck et al., 2002). The implication is that risk is increasingly assigned through technological interpretation rather than determined solely by individual traits. Understanding victimization patterns therefore requires attention to how digital infrastructures classify, sort, and prioritize users within data-driven systems (Eubanks, 2018; Pasquale, 2015, 2019).

4) Institutional Strain and Enforcement Asymmetry

Shifts in opportunity conditions also carry institutional implications, as law enforcement agencies, regulatory authorities, and platform face asymmetries in speed, scale, and adaptability when responding to AI-mediated crime (Brewer et al., 2019; Maimon & Louderback, 2019; Wall, 2024). Automated systems can generate deceptive content more rapidly than detection mechanisms can analyze it, while cross-jurisdictional digital interactions may further complicate attribution and enforcement. (Arnell & Faturoti, 2023; Schaefer & Mazerolle, 2017). These structural asymmetries do not merely hinder criminal investigation; they alter the strategic environment in which both offenders and guardians operate (Dupong & Whelan, 2021; Ekblom, 2017; Lavorgna, 2014).

Within the integrated analytical framework, such asymmetries can be interpreted as manifestations of weakened guardianship capacity (Bossler & Holt, 2009; Reyns, 2017; Williams, 2016). When detection systems struggle to match the pace of automated

offending, the structural balance described by RAT shifts in favor of offenders (Felson & Clarke, 1998; Pratt et al., 2010; Van Wilsem, 2011). At the same time, the behavioral dynamics emphasized by STT may reduce perceived deterrence, as actors interpret enforcement limitations as signals of reduced risk (Al Shamsi et al., 2023; Assarut et al., 2019; Jaishankar, 2008; Suler, 2004). Institutional strain therefore constitutes a systemic outcome of reconfigured opportunity conditions rather than an administrative shortcoming alone.

5) Normalization and Environmental Embedding

AI-mediated opportunity environments also foster the gradual normalization of deceptive interaction. As automated communication becomes more prevalent in digital spaces, distinguishing authentic from artificial engagement may become harder (Hancock & Bailenson, 2021; Varol et al., 2017). Over time, this ambiguity can alter expectations about online interaction, making manipulative or deceptive practices appear less anomalous. When deception becomes embedded within routine digital experience, it may be interpreted as an ordinary feature of the environment rather than as an exceptional event (Comes, 2025; Natale, 2024).

This normalization reflects the interplay of structural and behavioral dynamics. Extensive exposure to automated interaction reshapes how credibility is perceived and assessed (Goldsmith & Brewer, 2014; Stajano & Wilson, 2011), while altered perceptions expand the effectiveness of deceptive strategies (Modic & Anderson, 2015; Wikstrom & Kroneberg, 2022). The resulting feedback loop demonstrates that opportunity environments are not static contexts but evolving systems shaped by technological change and human adaptation (Broadhurst et al., 2021; Leukfeldt et al., 2017).

6) Systemic Interpretation of Cybercrime Outcomes

Taken together, the patterns described above suggest that contemporary cybercrime outcomes are best understood as systemic manifestations of reconfigured opportunity environments (Ekblom, 2017; Romagna & Leukfeldt, 2024; Wilcox et al., 2018). AI modifies the structural conditions under which crime occurs and simultaneously reshapes the behavioral responses of actors within those conditions (Caldwell et al., 2020; Fiorinelli & Zucca, 2025; Fleetwood, 2016; King et al., 2020). The observable consequences—patterns of victimization, differentiated harms, redistributed risk, institutional strain, and normalization of deception—reflect this dual transformation (Aebi et al., 2025; Farrell & Pease, 2017; Leukfeldt & Yar, 2016; Smith, 2026).

This interpretation shifts analytical focus away from individual incidents toward the broader environments in which those incidents become possible (Clarke, 1995; Cohen & Felson, 1979; Lee, 2010; Wortley & Townsley, 2016). It highlights that the significance of AI-mediated cybercrime lies not only in its technological novelty but in its capacity to reorganize the fundamental relationship between opportunity, behavior, and harm (Borgesano et al., 2025; Dupong & Whelan, 2021; Martineau et al., 2023; Miller, 2013). Such a perspective provides the con-

ceptual foundation for assessing the implications of these transformations for theory, governance, and institutional response.

The outcomes examined here demonstrate that AI reshapes cybercrime not only at the level of technique but at the level of systemic consequence. The final section considers the broader theoretical and practical implications of this transformation, including what the integrated framework contributes to criminological analysis and how it may inform responses to digitally mediated crime.

6. Implications and Conclusion

The analysis advanced in this study has argued that AI does not simply introduce new tools for cybercrime but fundamentally transforms the conditions under which such crime becomes possible. Integrating RAT and STT into a single analytical framework shows that contemporary cybercrime is better understood as the product of dynamically reconfigured opportunity environments than as a mere collection of isolated technological offenses. This reconceptualization shifts cybercrime from an incident-centered phenomenon to a systemic one, highlighting the interplay between structural conditions and behavioral processes within digitally mediated environments.

1) Theoretical Implications

The primary contribution of this study is conceptual. Existing criminological approaches to cybercrime have largely adopted single-theory frameworks that foreground either structural opportunity or behavioral transformation at the expense of their interaction (Holt & Bossler, 2016; Maimon & Louderback, 2019; Yar, 2005). While each approach captures important dimensions of digital offending, neither alone adequately explains the co-evolving relationship between technological infrastructure and human action characteristic of AI-mediated environments (Goldsmith & Brewer, 2015; Leukfeldt & Yar, 2016; Wall, 2024). The integrated RAT-STT framework developed here illustrates that structural opportunity and behavioral dynamics should be treated as mutually constitutive rather than analytically separable.

The implications of this reconceptualization extend beyond the present study to criminological theory more broadly. It suggests that technological change should not be approached as an external variable applied to existing models but as a condition capable of reshaping the explanatory architecture of those models themselves (Brantingham & Brantingham, 2018; Felson, 2016; Wikstrom & Kroneberg, 2022). In this sense, AI functions not merely as a contextual factor but as a structural-behavioral modulator that reorganizes the relationship between opportunity, agency, and constraint (Brewer et al., 2019; Opp, 2020; Cullen et al., 2008; Schaefer & Mazerolle, 2017). Recognizing this role allows established theories to be extended rather than replaced, preserving theoretical continuity while accommodating technological transformation.

2) Analytical Implications

Beyond its theoretical contribution, the integrated RAT-STT framework provides a systematic lens for interpreting diverse forms of cybercrime within a sin-

gle analytical structure. Conceptualizing crime as a recursive interaction among offenders, targets, guardians, and technological systems helps explain why AI-mediated offenses often appear scalable, adaptive, and resistant to traditional controls (Caldwell et al., 2020; King et al., 2020; Lee, 2010; McKay & Macintosh, 2024). These characteristics are not anomalies requiring entirely new categories of explanation; they are predictable consequences of environments in which opportunity conditions and behavioral dynamics are continuously reshaped by automated processes.

This perspective also highlights the importance of examining crime at the level of systems rather than incidents (Farrell & Pease, 2017). Individual cases may appear idiosyncratic or technologically novel, yet when analyzed within the integrated framework they reveal common underlying mechanisms (Holt & Bossler, 2016; Maimon & Louderback, 2019). Such an approach encourages comparative analysis across offense types and technological contexts, facilitating cumulative theoretical development as opposed to fragmented case-specific interpretation.

3) Institutional and Policy Implications

Although the present study is conceptual rather than prescriptive, its findings carry important implications for institutional and policy responses to contemporary cybercrime. Above of all, if digital offenses arise from reconfigured opportunity environments, interventions that focus exclusively on individual offenders or isolated incidents are unlikely to address their underlying causes. Effective responses must instead consider how technological infrastructures, platform architectures, and governance arrangements shape opportunity conditions (Dupong & Whelan, 2021; Wall, 2024). Measures that strengthen guardianship capacity, reduce structural asymmetries, or limit exploitability of digital environments may therefore be more effective than strategies oriented solely toward post hoc enforcement (Wortley & Townsley, 2016).

At the same time, the framework suggests that institutional responses should account for behavioral dynamics as well as structural conditions. Efforts to enhance user awareness, reduce susceptibility to manipulation, or increase perceived accountability can complement structural interventions by altering the behavioral context in which opportunities are interpreted and acted upon (Modic & Anderson, 2015; Reyns et al., 2011; Whitty, 2019). Approaches that address only one dimension risk producing adaptive responses in the other, underscoring the need for strategies that engage both simultaneously.

4) Limitations

Several limitations should be acknowledged. First, the framework developed here is theoretical in orientation and is not empirically tested within this article. While this conceptual focus allows the model to remain generalizable across technological contexts, empirical validation will be necessary to assess its explanatory scope and boundary conditions. Second, the analysis centers primarily on digitally mediated environments and therefore does not address how the integrated framework might apply to hybrid forms of crime that combine online and offline components. Third, the rapid evolution of AI tech-

nologies means that specific mechanisms discussed here may change over time, requiring ongoing refinement of theoretical models.

These limitations, however, reflect deliberate analytical choices rather than methodological shortcomings. The central aim of this study has been to clarify underlying conceptual relationships and to advance a framework capable of structuring future inquiry. Empirical research, comparative analysis, and domain-specific applications therefore represent logical extensions of this theoretical foundation.

5) Directions for Future Research

The integrated RAT-STT framework opens several avenues for future research. Empirical studies could examine how specific AI-mediated environments alter opportunity convergence or behavioral response patterns. Comparative analyses might investigate whether different technological architectures produce distinct configurations of structural and behavioral dynamics. Longitudinal research could explore how feedback processes between offenders, guardians, and technological systems evolve over time. Such work would not only test the propositions advanced here but also refine understanding of how digital environments shape crime more broadly. Future research may incorporate case-based, comparative, or data-driven analyses to empirically assess the applicability of the proposed framework across diverse cybercrime contexts.

Interdisciplinary collaboration will be particularly important in this regard. Because AI-mediated crime operates at the intersection of technological design, social interaction, and institutional governance, its analysis benefits from perspectives drawn from criminology, computer science, sociology, police science, law, psychology, and information studies. The framework proposed in this article is intended to support such dialogue by providing a shared conceptual vocabulary for analyzing technologically mediated offending.

7. Conclusion

This article has argued that AI marks not merely a technological development but a structural transformation in the ecology of crime. By integrating Routine Activity Theory and Space Transition Theory, it has demonstrated that contemporary cybercrime can be understood as an emergent outcome of dynamically reconfigured opportunity systems shaped by the interaction of technological infrastructure and human behavior. This perspective clarifies why AI-mediated offenses are increasingly scalable, adaptive, and resistant to traditional control mechanisms, and it highlights the need for analytical approaches that capture the systemic nature of digitally mediated crime.

The significance of this contribution lies not in proposing a new typology or regulatory framework but in offering a conceptual model (framework) capable of explaining how technological change reshapes the fundamental conditions of criminal activity. In doing so, the study seeks to advance criminological understanding of cybercrime while providing a foundation for future theoretical, empirical, and policy-oriented inquiry into crime in the age of AI.

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인공지능 시대의 사이버범죄 분석을 위한 RAT-STT(일상활동이론-공간전이이론) 통합 이론 모형

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인공지능(AI) 기술의 확산은 디지털 환경을 근본적으로 변화시키며, 범죄가 발생하는 조건 자체를 재구성하고 있다. 기존 연구는 기술의 발전이 범죄 수법에 미치는 영향에 주로 주목해 왔으나, 인공지능이 범죄 기회 구조 자체를 어떻게 변화시키는지에 대한 이론적 분석은 상대적으로 부족하였다. 이에 주목하여 이 연구는 일상활동이론(Routine Activity Theory)과 공간전이이론(Space Transition Theory)을 통합한 분석 틀(Framework)을 제시하여, 인공지능 매개 환경에서 구조적 기회 조건과 행태적 역동성이 어떻게 상호작용하는지를 설명한다. 여기서 제안된 통합 프레임워크는 인공지능을 단순히 범죄에 활용되는 도구가 아니라 범죄의 기회 구조와 행위 조건을 동시에 변화시키는 체계적 조절 요인으로 개념화한다. 이를 통해 현대 사이버범죄는 개별 기술 집약적인 범죄의 양태(樣態)가 아니라 동적으로 재구성된 기회 환경의 산물로 이해되어야 함을 논증한다. 이 연구는 기술 변화와 범죄 발생 간의 분석적 관계를 명확히 하려는 동시에, 다양한 디지털 범죄 현상을 설명할 수 있는 통합 개념 모형을 제시함으로써 사이버범죄 관련 학술 분야의 발전에 기여하려는 것이다. 이 논문은 실증 분석이나 규범적 정책 제안을 목적으로 하지는 않으며, 인공지능 시대에서 사이버범죄 연구를 위한 개념적 토대를 제공하는 데 그 궁극적 목표가 있다.

주요어: 인공지능(AI), 사이버범죄, 범죄 기회, 일상활동이론(RAT), 공간전이이론(STT), 기회 구조, 통합 개념 모형(프레임워크)