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Surveillance as a Socio-Technical System: Behavioral Impacts and Self-Regulation in Monitored Environments

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Abstract

Video surveillance systems have become pervasive in contemporary society, prompting growing concerns about their psychological and behavioral effects on individuals. This study investigates how perceived surveillance influences self-censorship and behavioral regulation in monitored environments, drawing on the conceptual framework of panoptic self-regulation and surveillance-induced anxiety. A structured questionnaire was administered to 358 university students, and data were analyzed using exploratory and confirmatory factor analysis to validate latent constructs, followed by ordinal logistic regression and mediation analysis to test key hypotheses. The results indicate that individuals who perceive higher psychological pressure due to surveillance are more likely to modify their behavior, exhibiting heightened self-awareness and restraint. Additionally, belief in the active monitoring of surveillance footage significantly amplifies behavioral vigilance. The perception of the technological omnipresence of surveillance further intensifies psychological discomfort, which mediates behavioral change. These findings conceptualize video surveillance as a socio-technical system that exerts behavioral influence through internalized psychological mechanisms. The study highlights the importance of considering the unintended consequences of surveillance technologies on autonomy and freedom, and it suggests that regulatory frameworks should account not only for legal compliance but also for the psychological impact of surveillance. The results provide empirical support for viewing surveillance systems as dynamic regulators of human behavior.

Keywords: video surveillance; psychological pressure; behavioral self-regulation; surveillance anxiety; surveillance systems; panoptic effect; socio-technical systems; systemic risks; surveillance capitalism

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1. Introduction

In contemporary society, video surveillance has emerged as a crucial tool for maintaining public safety, deterring criminal activity, and ensuring accountability in both private and public spaces [1–3]. Its deployment extends across urban centers, workplaces, transportation hubs, schools, and even personal residences, making it an omnipresent force in daily life [4–7]. However, this widespread use of surveillance technology raises a fundamental challenge: the delicate balance between security and individual freedom [8–10]. Research indicates that the extensive integration of video surveillance technology significantly influences individual behavior [11–13]. As such tools become embedded in various

aspects of daily life, individuals experience increased pressure to conform, avoiding actions that might be perceived as deviations from social norms [14–16]. In practice, these technologies limit opportunities for anonymous movement and access to services, thereby diminishing individuals' ability to remain unnoticed [17,18]. While surveillance serves the legitimate purpose of maintaining public order, as well as fulfilling other objectives explicitly outlined in Article 6 of the GDPR, its unchecked proliferation risks undermining the very liberties it aims to protect. This could lead to a society where human autonomy is subtly but profoundly eroded [19]. The establishment of a framework in which every action can potentially be recorded and analyzed places individuals in a context that infringes upon their fundamental need for privacy, even in public spaces [20,21].

1.1. Theoretical Framework

From a systems perspective, video surveillance should not be viewed in isolation as a technological artifact, but rather as a node within a larger cyber-physical-social system. It operates through dynamic feedback loops that connect technological infrastructure, legal norms, organizational practices, and human behavior [22–24]. The act of observation produces measurable psychological responses in individuals [25], which in turn alter public behavior patterns, thus shaping the very conditions surveillance is intended to monitor. These recursive interactions reflect the systemic nature of surveillance, wherein social inputs (such as perceived insecurity) lead to technical deployments (e.g., CCTV) [26], which then reconfigure social outputs (e.g., conformity, distrust, etc.), requiring new policy responses. This feedback mechanism makes surveillance a powerful regulator of social conduct, albeit one that may generate unintended consequences when not carefully designed and governed.

Michel Foucault's concept of the Panopticon, derived from Jeremy Bentham's [27] architectural model of a prison with constant observation, remains highly relevant in analyzing modern surveillance. In such a system, individuals internalize the awareness of being watched, leading to self-censorship and behavioral conformity. The ability to engage in spontaneous, unfiltered actions, one of the defining characteristics of personal freedom, is curtailed under the silent coercion of surveillance [28–30]. This results in what Hannah Arendt [31] described as the "loss of the public realm," wherein individuals no longer engage freely in discourse and action but instead operate within the constraints of a monitored society. Moreover, the psychological impact of constant surveillance fosters an environment of suspicion and alienation [32,33]. Trust, a fundamental element of social cohesion, is eroded when individuals perceive that their every move is being scrutinized [34]. This not only affects interpersonal relationships but also undermines democratic participation, as individuals may be deterred from political engagement due to fears of surveillance by state authorities or private entities [35–37].

In the language of systems theory, the behavioral effects of surveillance can be understood as emergent properties resulting from the interaction of system components—technological monitoring, regulatory structures, and individual cognition [23,38]. Surveillance thus functions not merely as a deterrent but as a form of distributed control, one that influences behavior not through direct enforcement but through the perceived risk of observation. The mere presence of surveillance infrastructure modifies the environment in which choices are made, steering individuals toward conformity without requiring active intervention. This embeddedness within daily environments illustrates the characteristics of self-regulating systems, wherein human behavior becomes an adaptive response to evolving systemic constraints.

The issue of video surveillance becomes even more concerning when viewed as just one component of the broader surveillance infrastructure embedded in society, with

potential chilling effects on the exercise of fundamental rights. According to Schauer's [39] theory of "chilling effects," government surveillance may deter individuals from engaging in legitimate or desirable online activities due to fears of legal repercussions or criminal sanctions, compounded by a lack of trust in the legal system's ability to protect their rights and innocence.

Expanding on this concept, Solove [40,41] broadened the chilling effects theory by examining the implications of modern surveillance and data collection. He argues that these practices function as a form of regulatory "environmental pollution", subtly shaping behavior by fostering an atmosphere in which individuals preemptively regulate their actions. His approach highlights how government monitoring of online activities cultivates a pervasive sense of conformity and self-censorship, ultimately constraining free expression and individual autonomy. The phenomenon of "social sorting", in which surveillance data are used to categorize and predict behaviors, exacerbates concerns related to discrimination and social stratification. This reinforces systemic biases and limits opportunities for marginalized groups [42,43].

Understanding surveillance as a socio-technical phenomenon benefits significantly from the conceptual lens of General Systems Theory (GST). Originating from the work of Ludwig von Bertalanffy [44], GST emphasizes the study of systems as organized wholes composed of interrelated and interdependent elements that operate through dynamic interactions. According to Bertalanffy [45], the traditional scientific approach relied heavily on reductionism, analyzing observable phenomena by decomposing them into elementary, isolated units. This method, while effective in controlled contexts, fails to account for emergent properties and feedback dynamics intrinsic to complex systems. In contrast, GST proposes a holistic framework in which natural, artificial, and social systems are seen as interconnected structures whose behavior cannot be understood by studying their parts in isolation but rather through the relationships and flows that bind them together.

From this perspective, surveillance is not simply a technological intervention or legal apparatus, but a multi-layered system involving human actors (data subjects, operators, regulators, etc.), technological infrastructures (CCTV, AI-based analytics, etc.), normative frameworks (such as the GDPR), and psychological or behavioral feedback loops. This integrated system functions not just through external enforcement but also by shaping internalized behaviors: individuals anticipate being observed and self-regulate accordingly [23].

Building on GST, Donella Meadows [46] deepens the understanding of systemic behavior through her influential work on feedback loops and leverage points. She describes systems as inherently adaptive, governed by reinforcing or balancing loops that stabilize or transform their behavior. In the context of surveillance, a balancing feedback loop is evident in how individuals alter their actions based on the perceived presence of monitoring, thereby stabilizing social order without explicit coercion. Meadows' notion of leverage points, places within a system where small shifts can produce significant systemic change, further suggests that altering public perception, enhancing institutional transparency, or modifying legal interpretations can significantly influence the surveillance ecosystem, often more effectively than technical regulation alone.

Expanding on the systems perspective, Niklas Luhmann [47] offers a sophisticated theory of social systems rooted in differentiation and communication. Rather than treating systems as stable entities, Luhmann views them as operations of distinction, existing only through the continuous differentiation between a system and its environment. A system, in this view, maintains its identity not by its components but by reproducing the difference that separates it from its surroundings. Luhmann identifies three types of systems—psychic, biological, and social—with social systems composed solely of communications. Human

beings, accordingly, belong to the environment of social systems, not to the systems themselves. This perspective is especially insightful for analyzing surveillance: it is not the mere presence of observers or technologies that defines surveillance systems, but the symbolic and communicative constructions that determine what is seen, recorded, or acted upon [48].

In the surveillance context, Luhmann's insight explains how monitoring practices construct and reinforce normative expectations [49]. Surveillance mechanisms do not only collect data; they communicate signals about acceptable behavior, deterrence, and deviance. This feedback fosters internalized control, a phenomenon aligned with Michel Foucault's [50] concept of the panopticon and compatible with Meadows' balancing loops.

As Jackson [51] observes, Luhmann's theory also accounts for the interactions between distinct systems, each operationally closed yet structurally responsive to environmental perturbations. Drawing on the work of Maturana and Varela [52], Luhmann introduces the idea of structural coupling and interpenetration to describe how systems—such as law, technology, or behavior—can influence one another through sustained mutual irritations. Though each system evolves based on its own logic, frequent interactions can lead to resonance, a condition where systems adapt in tandem, creating a form of stable co-dependency [53]. This is particularly applicable to the modern surveillance regime, where legal norms, technological capabilities, and social behaviors co-evolve, shaping and reshaping one another through ongoing informational and normative exchanges.

Taken together, these theorists provide a robust foundation for conceptualizing surveillance as a dynamic and evolving socio-technical system, rather than a static intervention [54]. Such systems function not only through formal regulatory mechanisms but also through psychological conditioning, symbolic influence, and the ongoing shaping of social norms and legal interpretations. To fully grasp the complexity of surveillance, analysis must extend beyond narrow legalistic or technical perspectives. Instead, an interdisciplinary approach is essential—one that integrates systems theory, behavioral psychology, data protection law, and ethics [23]. Surveillance technologies are never value-neutral; they encode assumptions about control, risk, and social order that shape both their design and implementation. Responding to their systemic consequences thus requires more than regulatory compliance. It demands adaptive governance models that include input from affected individuals, empirical data on behavioral effects, and human-centered design aligned with fundamental rights.

A broader conceptualization of surveillance as a socio-technical system demands regulatory responses that reflect its complexity and multi-dimensional impact. Legal instruments, while essential, are insufficient if they overlook the behavioral and psychological dynamics that surveillance environments produce. Therefore, normative frameworks must be embedded within adaptive and context-sensitive governance structures, ones capable of addressing not only the technological architecture of surveillance but also its effects on individual autonomy and social behavior. In this regard, the European Union's data protection framework offers a valuable model for balancing innovation with fundamental rights.

The General Data Protection Regulation [55], complemented by the guidelines of the European Data Protection Board [17] and the evolving case law of national Data Protection Authorities (DPAs), imposes clear constraints on the deployment of video surveillance. The foundational principles articulated in Article 5 of the GDPR, such as lawfulness, purpose limitation, and data minimization, function as legal safeguards designed to prevent surveillance practices that exert excessive psychological pressure or compromise individual dignity. These principles reflect a systemic approach to protecting privacy, ensuring that surveillance technologies do not undermine the essential conditions of human autonomy [56,57].

However, in real-world contexts, surveillance systems often produce unintended and problematic effects that extend beyond their initial technical or legal rationales. For instance, in workplace environments, continuous monitoring through CCTV or AI-based productivity tools can heighten psychological stress, suppress dissent, and undermine trust among colleagues, which are phenomena documented in recent organizational studies [7,16]. In urban public spaces, omnipresent surveillance disproportionately targets marginalized populations, such as racial minorities and unhoused individuals, contributing to spatial exclusion and discriminatory enforcement practices [6,10]. In educational settings, particularly in schools, surveillance technologies such as facial recognition, behavior-monitoring software, and biometric access systems have been shown to erode trust between students and educators, foster a climate of control and suspicion, and disproportionately discipline already vulnerable student group [58]. These dynamics are exacerbated by the normalization of data extraction in everyday life, where routine behaviors become the basis for algorithmic profiling and behavioral prediction.

A series of significant fines imposed by DPAs aim to curb and penalize surveillance practices deemed to exert disproportionate pressure, ultimately threatening individuals' right to privacy and anonymity. One of the most notable enforcement cases involved a EUR 10.4 million fine, in which the regulatory authority emphasized that companies must recognize that such intensive video surveillance constitutes a severe violation of employees' rights. Furthermore, it was underscored that video surveillance represents an especially intrusive infringement on personal rights, as it enables continuous observation and behavioral analysis [59].

However, there is no uniform case law among DPAs across EU member states, despite the fact that they apply the same regulation—the GDPR. This discrepancy reflects a lack of systemic coherence in regulatory enforcement, suggesting that the GDPR—though designed as a unified legal framework—functions within a fragmented implementation landscape. Such fragmentation underscores the need for interdisciplinary studies that approach surveillance not merely as a legal or technological issue but as an integral component of a broader socio-technical system. These studies should illuminate how surveillance practices operate within complex regulatory ecosystems, producing feedback loops between legal norms, psychological responses, and institutional behavior. The right to privacy is intrinsically linked to fundamental aspects of human dignity, such as autonomy, self-esteem, and the freedom to act without unwarranted scrutiny—each of which can be impacted by the systemic dynamics of surveillance. Research on regulatory enforcement emphasizes the crucial role of national DPAs in shaping GDPR compliance through case law and administrative decisions [60,61], but also reveals how divergent interpretations disrupt system-level consistency. Therefore, this study seeks to provide interdisciplinary arguments that could contribute to the development of a more integrated and coherent practice for ensuring data protection compliance within the system of video surveillance governance.

1.2. Research Objectives

Grounded in the theoretical framework of behavioral self-censorship under surveillance [50,62,63] and recent studies on the psychological impact of perceived surveillance [64], this study seeks to move beyond simplistic cause–effect models and explore the systemic nature of surveillance-induced self-regulation. While previous research has acknowledged the psychological effects of being watched, there remains a gap in empirically disentangling how perceived surveillance, psychological pressure, and behavioral modification interact within broader socio-technical systems. The central research question guiding this investigation is therefore the following: *To what extent does the perception of video surveillance generate psychological pressure that mediates behavioral self-regulation in monitored*

environments, and how do these effects function as emergent properties of a cyber-physical-social system? This question reflects an interdisciplinary interest in understanding how surveillance operates not merely as a technical apparatus or legal instrument but as a dynamic feedback mechanism embedded in everyday life, shaping individual behavior through anticipatory adaptation and internalized norms. By framing surveillance as a system with recursive effects, the study aims to contribute to both theoretical models and practical governance approaches that account for the behavioral consequences of technologically mediated observation.

The study investigates how surveillance shapes behavior through three key constructs: perceived omnipresence of surveillance, psychological pressure, and behavioral modification. Each of these constructs was conceptualized and operationalized based on prior empirical and theoretical literature.

Psychological pressure captures the internal emotional or cognitive stress experienced due to the awareness of being surveilled. It includes feelings of discomfort, anxiety, or tension arising from the perception that one's actions may be scrutinized or misinterpreted. This construct is grounded in the panopticism literature [16,64], which posits that perceived surveillance—even without active intervention—triggers anticipatory self-control [65–67].

Behavioral modification reflects the extent to which individuals consciously alter their actions, expressions, or decisions in response to being surveilled. It is conceptualized as a form of adaptive self-regulation or self-censorship, rooted in the work of Westin [68] and Solove [41], and further developed in empirical studies on conformity under surveillance [11,69].

Perceived omnipresence of surveillance refers to the degree to which individuals believe that surveillance systems (e.g., CCTV or digital monitoring) are functioning in real time, actively monitored, and capable of identifying specific persons. This construct draws from theories of symbolic surveillance [32,50] and relates to the perceived efficacy and presence of observation systems. Recent studies highlight how the perceived capability of AI-powered surveillance tools, including facial recognition and behavioral analytics, enhances this sense of constant observation [70–72].

Each construct was measured using multiple Likert-scale items adapted from validated instruments or developed in line with prior studies and subjected to factor analysis to confirm construct validity. This structured approach allows for a nuanced examination of the mechanisms through which surveillance exerts psychological and behavioral effects.

Objective 1. *The Impact of Perceived Psychological Pressure on Behavioral Modifications.*

This objective seeks to determine the extent to which individuals modify their behavior in response to the psychological pressure induced by video surveillance. It focuses on two key aspects [Appendix A]:

H1. *The effect of perceived psychological pressure on behavioral modifications.*

According to the theory of self-censorship and the panoptic effect [50], individuals who experience heightened psychological pressure due to surveillance tend to regulate their actions to conform to perceived social expectations or avoid negative judgments. This study operationalizes perceived psychological pressure as Factor 1 (aggregating Items 9, 11, and 13), which captures respondents' discomfort and awareness of constant monitoring. Behavioral modifications are assessed through Factor 2 (Items 7, 8, and 10), which examines the extent to which individuals alter their actions, exhibit greater self-awareness, or suppress certain behaviors in response to surveillance. If a significant relationship is found, it will support the notion that the mere awareness of being watched influences people's actions, reinforcing the concept of panoptic self-regulation in contemporary surveillance environments.

H2. *The effect of belief in active surveillance on behavioral vigilance.*

Beyond general psychological pressure, the study also examines whether individuals' perception that video recordings are actively monitored (Item 5) heightens behavioral vigilance in surveilled spaces (Item 7). Social control theory [73] suggests that when individuals believe they are under direct and active scrutiny, they are more likely to engage in self-regulation to avoid potential repercussions. This hypothesis investigates whether respondents who strongly believe that surveillance footage is reviewed exhibit increased attentiveness to their own behavior, reinforcing the link between perceived oversight and behavioral control mechanisms.

Objective 2. *The Influence of Perceived Omnipresence of Surveillance and Mediation Effects.*

This objective expands the investigation to examine how the perception of pervasive surveillance intensifies psychological pressure and how this pressure mediates behavioral changes. Specifically, it addresses the following effect.

H3. *The role of perceived technological omnipresence in amplifying psychological pressure.*

The recent literature [63,64,74] highlights that advancements in surveillance technology have contributed to a widespread perception that monitoring is no longer localized or situational but rather continuous and inescapable. This hypothesis tests whether individuals who strongly believe in the omnipresence of surveillance technologies (Item 15) report higher levels of psychological pressure associated with video monitoring (Factor 1: Items 9, 11, 13). If a significant relationship is found, it will indicate that the mere perception of being constantly observable, even without direct evidence of monitoring, heightens psychological distress, supporting the argument that technological surveillance generates a persistent state of self-regulation.

H4. *The mediation effect of immediate psychological pressure on behavioral modifications.*

Building upon H1, this hypothesis introduces a mediation model to examine whether immediate psychological pressure experienced during daily activities (Item 9) serves as a conduit through which the pressure of having one's lifestyle monitored (Item 13) leads to behavioral modifications (Item 10). Staples [2] suggests that surveillance-related anxiety does not always directly alter behavior but may do so through intermediate emotional and cognitive responses.

If the mediation effect is confirmed, it would support the notion that surveillance-induced behavioral changes are not necessarily the result of a direct cause-effect relationship but rather emerge through a progressive psychological process where macro-level surveillance concerns (e.g., lifestyle monitoring) lead to heightened real-time discomfort (psychological pressure during daily activities), which ultimately results in behavioral self-regulation in surveilled spaces.

2. Materials and Methods

2.1. Participants

The present study employed a survey-based methodology, administering a structured questionnaire to undergraduate and master's students. From a total student population of 5132, a sample of 358 participants was obtained.

Prior to administering the questionnaire, a G*Power 3.1.9.7 analysis was conducted to determine the minimum required sample size for ordinal logistic regression. The two-tails analysis was performed using the following parameters: $\alpha = 0.05$, power $(1 - \beta) = 0.80$,

odds ratio = 1.5, and P(Y = 1 | X = 1) = 0.5. With these, we assumed that the event of interest had an equal probability of occurring in the presence of the predictor. Additionally, Nagelkerke's R^2 was set at 0.4, indicating a relatively strong model and a commonly accepted value in studies of this nature [75]. The choice of Nagelkerke's R^2 at 0.4 was made considering that other factors, not included in the study, may also influence the variation in the dependent variable. This is a common occurrence, given that phenomena of this type are typically influenced by multiple factors that are difficult to quantify.

The analysis determined the required sample size of 346 participants.

The final sample comprised individuals aged 18 to 57 years (M = 23.54, SD = 7.387). The gender distribution was 73.5% female and 26.5% male. While this demographic composition provides valuable insights into how young adults—particularly women—experience and interpret video surveillance, it also introduces certain limitations regarding the generalizability of the findings. University students may be more digitally literate, privacy-aware, and psychologically attuned to surveillance-related issues than the general population. Moreover, the gender imbalance in the sample warrants careful interpretation, as prior research suggests that women may experience higher levels of surveillance-related discomfort and are more likely to modify their behavior in monitored settings due to heightened social and safety concerns [76,77]. Therefore, although the sample is appropriate for exploring patterns of perceived psychological pressure and behavioral adaptation in surveilled environments, future studies should aim to replicate the findings in more diverse populations—including different age groups, occupational contexts, and more balanced gender distributions—to enhance external validity and capture broader systemic dynamics.

All procedures involving human participants complied with institutional ethical guidelines and conformed to the ethical standards outlined in the 1964 Helsinki Declaration and its subsequent amendments. To ensure compliance with ethical standards and protect participant confidentiality, no personal data were collected. Prior to participation, respondents received detailed information regarding the anonymous nature of their responses and their right to voluntary participation.

No material incentives or other forms of compensation were offered to participants.

2.2. Design

Factor analysis identified three latent factors with an Average Variance Extracted (AVE) of 0.729 for Perceived Pressure, 0.700 for Behavioral Modification, and 0.548 for Perceived Omnipresence of Surveillance. Confirmatory analysis validated the model, achieving a Goodness-of-Fit Index (GFI) of 0.998 and a Root Mean Square Error of Approximation (RMSEA) of 0.063. Ordinal logistic regression was used to test hypotheses. Model reliability was confirmed with Cronbach's Alpha values of 0.835 and 0.836 for the two main factors.

To assess the potential influence of Common Method Bias (CMB), a first confirmatory model was tested, specifying a single latent factor that included all items considered in the analysis. This approach follows the recommendations of Podsakoff [78], who argue that a good model fit in such a single-factor solution may indicate the presence of systematic bias in the data structure. The results revealed a partially acceptable fit based on the CFI (0.942) and TLI (0.919) indices; however, the RMSEA value was high (0.169), substantially exceeding the acceptable threshold of 0.08. This outcome suggests that the data cannot be adequately explained by a single common factor and that the relationships among variables are not significantly influenced by common method bias. Thus, the factorial structure is likely to reflect genuine distinctions between the theoretical constructs rather than being driven by a shared methodological source of variance.

In addition, an extended structural model was estimated that incorporated, alongside the three theoretical constructs, a latent common method factor (CMB) loading on all items.

In this extended model, the SRMR value was 0.302—well above the acceptable threshold of 0.08 [79]—indicating a substantial mismatch between the model and the data. This result, combined with CFI values ranging from 0.839 to 0.908 and RMSEA values between 0.094 and 0.066, indicates that including the CMB factor did not improve model fit. On the contrary, the findings support the absence of significant common method bias.

This questionnaire was designed to assess various aspects identified in the academic literature, European Data Protection Board (EDPB) guidelines, and Data Protection Authorities (DPA) case law as potential risks associated with widespread video surveillance. The questionnaire employs a five-point Likert scale to capture respondents' perceptions and behaviors.

The first category of items evaluates respondents' interest in the existence of video surveillance in their surroundings (Item 1) and their self-assessed knowledge of the conditions under which video surveillance cameras can be installed (Item 2).

The second category measures respondents' actions regarding video surveillance, ranging from requesting information about the legality of camera installations (Item 3) to formally contesting being recorded by a surveillance camera (Item 4).

A latent factor capturing the perceived likelihood of identification through video surveillance was constructed by aggregating Items 5 and 6. This factor reflects respondents' perceptions of the extent to which recorded video footage may be analyzed and used to identify individuals.

Another latent factor measuring the perceived pressure of continuous surveillance and the limitation of anonymity was developed by aggregating Items 9, 11, and 13. This factor aims to capture the extent to which respondents feel constrained by the omnipresence of surveillance cameras, limiting their ability to remain unnoticed in public spaces.

A third factor, assessing behavioral modifications in surveilled spaces, was created by aggregating Items 7, 8, and 10. This factor reflects respondents' tendency to alter their behavior in response to video surveillance, either by becoming more self-conscious about their actions or by actively modifying their conduct to conform to perceived social norms.

The final category of items examines respondents' attitudes toward the generalization of video surveillance. Item 14 assesses the extent to which respondents perceive continuous surveillance as a means of enhancing security, measuring their level of comfort with the idea of being monitored throughout their daily activities. Item 15 evaluates the acceptance of the notion that, due to technological advancements, privacy and confidentiality have become obsolete, capturing respondents' broader perspectives on the implications of surveillance in contemporary society.

2.3. Procedure

Students were informed about the study through the online portals of their respective university departments and faculties. They were provided with details regarding the estimated completion time of 5–7 min and were assured that the collected data would be processed solely for scientific purposes. Additionally, they were explicitly informed that personal data would not be disclosed and that respondents' email addresses were not collected.

The questionnaire was administered individually without the intervention of an interviewer. The data collection method employed was Computer-Assisted Web Interviewing (CAWI). This method was chosen in alignment with the research objectives, considering the target audience's accessibility to and preference for digital technology.

The questionnaire consisted exclusively of mandatory questions. To ensure data reliability, response patterns were examined for inconsistencies, particularly in cases where answers to positively and negatively worded items contradicted each other in an implausi-

ble manner. Furthermore, the questionnaire was optimized for mobile devices to enhance accessibility and ease of completion.

2.4. Data Analysis

2.4.1. Factor Analysis

To explore the latent structure of the item set and validate the proposed factorial model, we conducted an exploratory factor analysis (EFA), followed by a confirmatory factor analysis (CFA).

For the EFA, the factor extraction method used was Principal Axis Factoring (PAF) with Promax rotation. The analysis was based on a polychoric correlation matrix, which more accurately models relationships among ordinal items.

To assess sample adequacy, we employed the Kaiser–Meyer–Olkin (KMO) test, which yielded a value of 0.839, indicating a very good fit for factor analysis. To verify the presence of significant correlations among the variables, Bartlett's test of sphericity was applied. The test result showed a significance level of $p < 0.001$, suggesting that the data are suitable for factor analysis. In conclusion, the obtained KMO value and the significance level of Bartlett's test confirm that factor analysis was both appropriate and justified.

Based on the factor loadings of the items on the factors identified by the EFA, as well as the research context, we identified three latent factors: Factor 1 (Perceived Pressure)—Items 9, 11, 13; Factor 2 (Behavioral Modification)—Items 7, 8, 10; Factor 3 (Perceived Omnipresence of Surveillance)—Items 5, 6. Considering that the research variables are ordinal, the Weighted Least Squares Mean and Variance adjusted (WLSMV) estimator was used to determine the CFA indicators, as it is the most appropriate for the data structure. The following results were obtained. The model fit indices suggest an acceptable fit. The chi-square value for the model was significant, $\chi^2(17) = 41.182$, $p < 0.001$, with a χ^2/df ratio of 2.422, indicating an adequate model fit to the data. The Goodness-of-Fit Index (GFI) was 0.998, suggesting a good fit between the hypothesized model and the observed data. The Comparative Fit Index (CFI) was 0.993, the Normed Fit Index (NFI) was 0.988, and the Tucker–Lewis Index (TLI) was 0.989, all of which indicate a strong model fit. Additionally, the Root Mean Square Error of Approximation (RMSEA) was 0.063, suggesting an acceptable model fit. The Standardized Root Mean Square Residual (SRMR) was 0.028, which indicates a strong model fit. Given that the model involves factors in the analysis, the Average Variance Extracted (AVE) indicator was used to assess convergent validity. The AVE values obtained were Factor 1 = 0.729, Factor 2 = 0.700, and Factor 3 = 0.548, indicating an adequate level of convergent validity. Additionally, to evaluate discriminant validity, the Heterotrait–Monotrait Ratio (HTMT) indicator was used. The HTMT values were Factor 1 $\leftrightarrow$ Factor 2 = 0.848, Factor 1 $\leftrightarrow$ Factor 3 = 0.254, Factor 2 $\leftrightarrow$ Factor 3 = 0.370. These values suggest an acceptable level of discriminant validity, indicating that the factors are sufficiently distinct from one another.

Overall, these indices support the validity of the three latent factors in explaining the underlying factors that govern individuals' psychological responses and behavioral adjustments in surveilled environments, confirming the robustness of the proposed factorial structure.

As an indicator of the internal reliability of the item sets forming the factors, Cronbach's Alpha was calculated for each factor and yielded the following results: Factor 1: $\alpha = 0.835$; Factor 2: $\alpha = 0.836$; Factor 3: $\alpha = 0.587$. The first two factors exhibit values greater than 0.8, indicating very good reliability.

For Factor 3, which consists of only two items, the Cronbach's Alpha value is naturally lower and does not carry significant interpretative weight. As a result, the items within this factor were not used as an aggregated latent variable. However, the relatively high

reliability index, even for a factor with only two items, suggests that they share meaningful common content.

2.4.2. Hypothesis Modeling

To test the proposed hypotheses, the following statistical models were employed:

H1. *An ordinal logistic regression is conducted, where Factor 1 serves as the predictor, and Factor 2 is the dependent variable.*

H2. *An ordinal logistic regression is performed, with Item 5 as the predictor and Item 7 as the dependent variable.*

H3. *An ordinal logistic regression is applied, where Item 15 serves as the predictor, and Factor 1 is the dependent variable.*

H4. *A mediation analysis using ordinal logistic regression is conducted. Item 13 serves as the predictor, Item 9 as the mediator, and Item 10 as the dependent variable.*

H4a. *An ordinal logistic regression is applied, where Item 13 serves as the predictor, and Item 10 is the dependent variable.*

H4b. *An ordinal logistic regression is applied, where Item 13 serves as the predictor, and Item 9 is the dependent variable.*

H4c. *An ordinal logistic regression is applied, where Item 9 serves as the predictor, and Item 10 is the dependent variable.*

H4d. *An ordinal logistic regression is applied, where Item 13 and Item 9 serve as predictors, and Item 10 is the dependent variable.*

Before conducting the ordinal logistic regression analysis, key assumptions were verified to ensure the validity of the model.

The choice of ordinal logistic regression was guided by the nature of the dependent variables, which were measured using ordinal Likert-type scales. This modeling technique is well suited for evaluating the relationships between the included predictors and ordinal outcomes while also preserving the rank order of responses. It also enables estimation of the odds of transitioning to higher levels of behavioral modification as a function of variations in psychological pressure or perceived surveillance awareness. The proportional odds assumption was tested and confirmed for all models, ensuring the consistency and stability of estimated effects across response thresholds.

Mediation analysis within the ordinal regression framework was employed to examine the pathways through which surveillance-related concerns influence behavioral responses via psychological pressure. This approach aligns with recent methodological literature that advocates for the use of mediation models to better understand causal mechanisms in social–psychological research involving non-continuous data [75,80]. To ensure the robustness of the results, bootstrap resampling with 10,000 iterations was conducted—an established technique for estimating indirect effects and confidence intervals in mediation analysis.

For the interpretation of the obtained values, the following significance thresholds were applied. A p-value < 0.05 in the Model Fitting Information test indicates that the model with predictors provides a significantly better fit than the null model. A p-value > 0.05 in the Goodness-of-Fit test suggests that the selected model adequately represents the data. Likewise, a p-value > 0.05 in the Test of Parallel Lines confirms that the predictor

coefficients remain stable across all threshold levels, thereby supporting the proportional odds assumption.

The Pseudo R-Square values offer an indication of the extent to which predictor variability explains the variance in the dependent variable. While these values do not have a direct interpretation equivalent to R^2 in linear regression, they serve as a general measure of model acceptability. Additionally, given that Pearson's test is highly sensitive to small or zero-frequency cells, it may tend to reject otherwise valid models. Regarding the acceptance of the H4b model, the observed Pseudo R-Square values, along with the significance level of the Deviance test, provide robust statistical justification for considering the model appropriate.

Data presented in Table 1 confirm that all required conditions for implementing the proposed models have been met, further supporting their validity and applicability within the research framework.

Table 1. Model fit evaluation of the ordinal logistic regression analysis.

	Model Fitting Information		**Goodness-of-Fit**				**Pseudo R-Square**		**Test of Parallel Lines**	
			Pearson		**Deviance**					
	Chi-Square	***p***	**Chi-Square**	***p***	**Chi-Square**	***p***	**Nagelkerke**	**McFadden**	**Chi-Square**	***p***
H1	250.056	0.000	157.414	0.194	136.190	0.644	0.507	0.148	15.945	0.143
H2	25.274	0.000	23.273	0.079	20.675	0.148	0.072	0.024	4.173	0.243
H3	5.473	0.019	60.130	0.095	63.758	0.052	0.015	0.004	16.552	0.122
H4a	148.344	0.000	16.343	0.360	17.418	0.294	0.362	0.149	2.262	0.520
H4b	186.090	0.000	31.383	0.008	22.599	0.093	0.432	0.185	2.619	0.454
H4c	225.307	0.000	10.149	0.810	9.095	0.873	0.498	0.227	1.665	0.645
H4d	246.532	0.000	95.672	0.321	76.715	0.840	0.531	0.248	5.836	0.442

3. Results

To test H1, H2, and H3, ordinal logistic regression analyses were performed under the proportional odds assumption, utilizing the Logit function.

The results of the ordinal logistic regression model for H1 (Table 2) confirm the statistical significance of both the predictor and the threshold estimates. The threshold values (αj) indicate the cumulative log-odds of transitioning between adjacent categories of the dependent variable. These estimates progressively increased from $\alpha_3 = 1.240$ (SE = 0.235, $p < 0.001$) to $\alpha_{14} = 9.562$ (SE = 0.635, $p < 0.001$), highlighting the ordered nature of the dependent variable. The standard errors of the thresholds gradually increased at higher response levels, suggesting a limited number of observations in extreme categories, which is a common occurrence in ordinal logistic regression. The widening of the confidence intervals for higher thresholds further reflects this pattern, indicating greater variability in these regions.

The predictor coefficient ($\beta = 0.603$, SE = 0.042, Wald = 201.783, $p < 0.001$) confirms a statistically significant relationship between the independent and dependent variables. The positive coefficient suggests that an increase in the predictor is associated with higher odds of transitioning to a superior category. The significance of the Wald test and the relatively narrow confidence interval (CI = [0.520, 0.686]) reinforce the robustness of this effect.

To verify the stability of the model, the PROCESS macro for SPSS v.28 [80] was applied using 10,000 bootstrap resamples with bias correction. The analysis of the obtained results indicates that only one bias exceeded 0.1, corresponding to the last threshold (α_{14}). This discrepancy is solely attributed to the limited number of observations near this threshold. Furthermore, an additional argument supporting the model's reliability is that the predictor coefficient exhibited a very small bias of 0.005, reinforcing the overall stability of the estimates.

Table 2. Ordinal logistic regression results for H1.

		Estimate	SE	Wald Test	*p*	CI 95%	
						LL	UL
Threshold (α_j)	3	1.240	0.235	27.843	0.000	0.780	1.701
	4	1.910	0.233	67.304	0.000	1.454	2.366
	5	2.367	0.238	99.107	0.000	1.901	2.833
	6	3.079	0.254	146.917	0.000	2.581	3.577
	7	3.851	0.280	188.816	0.000	3.302	4.400
	8	4.512	0.307	215.587	0.000	3.910	5.115
	9	5.474	0.353	240.692	0.000	4.783	6.166
	10	6.416	0.404	252.747	0.000	5.625	7.207
	11	7.196	0.451	255.062	0.000	6.313	8.080
	12	7.873	0.495	252.922	0.000	6.903	8.843
	13	9.055	0.586	238.803	0.000	7.907	10.204
	14	9.562	0.635	226.624	0.000	8.317	10.806
Location (β)		0.603	0.042	201.783	0.000	0.520	0.686

The overall pattern of results supports the proportional odds assumption, as the predictor's effect appeared stable across different levels of the dependent variable. However, the increasing standard errors for higher thresholds indicate a potential data sparsity issue in these extreme categories.

These findings confirm that the predictor exerted a meaningful influence on the dependent variable, demonstrating a clear and statistically significant effect. The model appears well fitted, and while the sparsity of observations in extreme categories may introduce some variability, the overall estimates remain stable and reliable.

Figure 1 provides a graphical interpretation of the Logit coefficient, illustrating that for a one-unit increase in the predictor, the odds of transitioning to a higher category in the dependent variable increase by approximately 1.83 times.

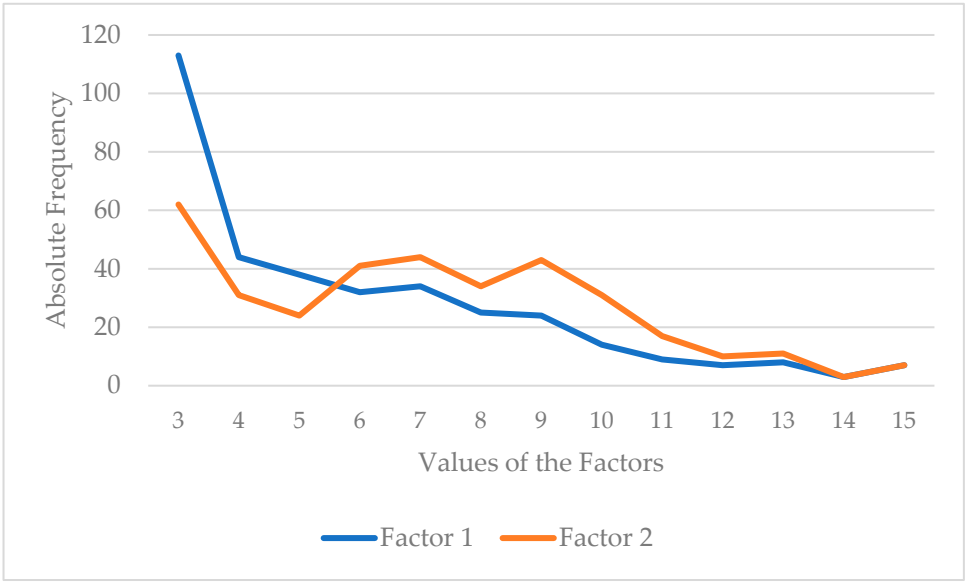


Figure 1. Absolute frequency values for Factor 1 and Factor 2.

The results of the ordinal logistic regression analysis for H2 (Table 3) confirm the statistical significance of both the predictor and the majority of the threshold estimates. The threshold values define the cumulative log-odds for transitioning between adjacent categories of the dependent variable. While the first threshold ($\alpha_1 = 0.493$, $p = 0.138$) is

not statistically significant, indicating a weaker distinction between the lower response categories, the subsequent thresholds are highly significant at $p < 0.001$, reinforcing the ordered nature of the dependent variable. The progressive increase in threshold values suggests a clear transition between response levels, with larger differences observed at the upper categories, which aligns with the expectations of an ordinal model.

Table 3. Ordinal logistic regression results for H2.

		Estimate	SE	Wald Test	*p*	CI 95%	
						LL	UL
Threshold (α_j)	1	0.493	0.332	2.206	0.138	−0.158	1.144
	2	1.419	0.337	17.697	0.000	0.758	2.079
	3	2.900	0.364	63.341	0.000	2.186	3.614
	4	4.652	0.428	118.229	0.000	3.814	5.491
Location (β)		0.534	0.104	26.381	0.000	0.330	0.738

The predictor coefficient (β = 0.534, SE = 0.104, Wald = 26.381, $p < 0.001$) indicates a strong and statistically significant effect. The positive coefficient suggests that an increase in the predictor is associated with a higher probability of transitioning to a superior category of the dependent variable. The confidence interval (0.330–0.738) does not include zero, further confirming the robustness of the estimated relationship.

To assess model stability, a bootstrap analysis with 10,000 resamples was conducted. The results indicate that all bias values are below 0.05, both for the threshold estimates and the predictor coefficient, suggesting that the model provides stable and reliable estimates without significant distortions introduced by resampling.

A relevant aspect that may influence the interpretation of the results is the imbalanced distribution of the predictor across the categories of the dependent variable. In the first category, the predictor accounts for only 2% of the total observations, which may affect the precision of estimates at this level. This unequal distribution may explain the lack of significance for the first threshold, suggesting a possible aggregation of observations in the upper categories and a potential need to reconsider the granularity of the lower levels.

Overall, the results support the proportional odds assumption, as the predictor's effect remains stable across all categories of the dependent variable. However, the non-significance of the first threshold, combined with the low representation of the predictor in the lowest category, may indicate a tendency for response clustering in the higher levels.

The results of the ordinal logistic regression model for H3 (Table 4) confirm the statistical significance of the predictor and most of the threshold estimates.

The threshold values exhibited a progressive increase from $\alpha_3 = 0.022$ (SE = 0.366, $p = 0.952$) to $\alpha_{14} = 4.748$ (SE = 0.528, $p < 0.001$), emphasizing the ordered nature of the dependent variable. The standard errors of the thresholds tended to increase at higher response levels, particularly for α_{14}, where the SE reached 0.528. This pattern suggests a reduced number of observations in extreme categories, a common characteristic in ordinal logistic regression. The broadening of confidence intervals for higher thresholds (e.g., the CI for α_{14} was [3.714, 5.782]) further reflects this trend, indicating increased variability in these regions.

The predictor coefficient (β = 0.222, SE = 0.096, Wald = 5.349, $p = 0.021$) established a statistically significant relationship between the independent and dependent variables. The positive coefficient suggests that an increase in the predictor variable is associated with higher odds of transitioning to a superior category. The significance of the Wald test, coupled with the confidence interval (CI = [0.034, 0.411]), reinforces the robustness of this effect, though the magnitude of influence remains moderate.

Table 4. Ordinal logistic regression results for H3.

		Estimate	SE	Wald Test	*p*	CI 95%	
						LL	UL
Threshold (α_j)	3	0.022	0.366	0.004	0.952	−0.695	0.739
	4	0.553	0.366	2.273	0.132	−0.166	1.271
	5	0.985	0.369	7.121	0.008	0.261	1.708
	6	1.361	0.372	13.374	0.000	0.632	2.091
	7	1.807	0.377	22.932	0.000	1.068	2.547
	8	2.198	0.383	32.887	0.000	1.447	2.950
	9	2.685	0.393	46.590	0.000	1.914	3.456
	10	3.077	0.405	57.779	0.000	2.284	3.871
	11	3.415	0.418	66.701	0.000	2.595	4.234
	12	3.767	0.437	74.417	0.000	2.911	4.622
	13	4.381	0.485	81.538	0.000	3.430	5.332
	14	4.748	0.528	80.971	0.000	3.714	5.782
Location (β)		0.222	0.096	5.349	0.021	0.034	0.411

While the proportional odds assumption appeared to hold overall, the increasing standard errors for higher thresholds indicate potential sparsity in extreme response categories. Nevertheless, the findings confirm that the predictor exerted a meaningful and statistically significant effect on the dependent variable.

The mediation analysis applied within the ordinal logistic regression framework confirmed significant relationships between the predictor, mediator, and dependent variable. The direct effect of the predictor on the dependent variable (H4a) ended up being significant (β = 1.108, SE = 0.099, Wald = 125.847, $p < 0.001$, CI = [0.914, 1.302]), indicating a strong positive influence (Table 5).

Table 5. Ordinal logistic regression results for H4a.

		Estimate	SE	Wald Test	*p*	CI 95%	
						LL	UL
Threshold (α_j)	1	1.396	0.202	47.604	0.000	0.999	1.792
	2	2.726	0.238	131.022	0.000	2.259	3.192
	3	5.013	0.355	199.827	0.000	4.318	5.708
	4	6.086	0.419	210.951	0.000	5.265	6.907
Location (β) 4a		1.108	0.099	125.847	0.000	0.914	1.302

The relationship between the predictor and mediator (H4b) was even stronger (β = 1.291, SE = 0.105, Wald = 151.503, $p < 0.001$, CI = [1.085, 1.496]) (Table 6), while the effect of the mediator on the dependent variable (H4c) was the most pronounced (β = 1.430, SE = 0.108, Wald = 174.699, $p < 0.001$, CI = [1.218, 1.642]) (Table 7).

The inclusion of additional predictors (H4d) (Table 8) revealed that Item 9 (β = 1.157, SE = 0.121, Wald = 92.095, $p < 0.001$, CI = [0.921, 1.393]) had a greater impact on the dependent variable than Item 13 (β = 0.513, SE = 0.112, Wald = 21.087, $p < 0.001$, CI = [0.294, 0.732]).

Bootstrap resampling (10,000 iterations, Tables 9–12) confirmed the stability of the estimates, with minimal bias and consistent confidence intervals.

These findings support the validity of the mediation model and indicate a significant indirect effect of the predictor on the dependent variable through the mediator, reinforcing the hypothesis that intermediary mechanisms play a crucial role in the relationship between variables.

Table 6. Ordinal logistic regression results for H4b.

		Estimate	SE	Wald Test	p	CI 95%	
						LL	UL
Threshold (α_j)	1	1.966	0.215	83.960	0.000	1.546	2.387
	2	3.078	0.250	151.113	0.000	2.587	3.568
	3	5.100	0.354	207.192	0.000	4.405	5.794
	4	6.020	0.404	221.944	0.000	5.228	6.812
Location (β) 4b		1.291	0.105	151.503	0.000	1.085	1.496

Table 7. Ordinal logistic regression results for H4c.

		Estimate	SE	Wald Test	p	CI 95%	
						LL	UL
Threshold (α_j)	1	2.110	0.228	85.910	0.000	1.664	2.556
	2	3.658	0.281	169.428	0.000	3.108	4.209
	3	6.322	0.424	222.169	0.000	5.491	7.153
	4	7.591	0.497	233.520	0.000	6.617	8.564
Location (β) 4c		1.430	0.108	174.699	0.000	1.218	1.642

Table 8. Ordinal logistic regression results for H4d.

		Estimate	SE	Wald Test	p	CI 95%	
						LL	UL
Threshold (α_j)	1	2.491	0.249	100.458	0.000	2.004	2.979
	2	4.104	0.306	179.881	0.000	3.504	4.703
	3	6.929	0.465	222.390	0.000	6.019	7.840
	4	8.259	0.544	230.645	0.000	7.193	9.325
Location (β) 4d Item 9		1157	0.121	92.095	0.000	0.921	1.393
Location (β) 4d Item 13		0.513	0.112	21.087	0.000	0.294	0.732

Table 9. Bootstrap ordinal logistic regression results for H4a.

	Estimate	Bias	SE	CI 95%	
				LL	UL
Location (β) 4a	1.108	0.008	0.107	0.916	1.334

Table 10. Bootstrap ordinal logistic regression results for H4b.

	Estimate	Bias	SE	CI 95%	
				LL	UL
Location (β) 4b	1.291	0.011	0.119	1.077	1.545

Table 11. Bootstrap ordinal logistic regression results for H4c.

	Estimate	Bias	SE	CI 95%	
				LL	UL
Location (β) 4c	1.430	0.012	0.121	1.213	1.694

Table 12. Bootstrap ordinal logistic regression results for H4d.

	Estimate	Bias	SE	CI 95%	
				LL	UL
Location (β) 4d Item 9	1.157	0.010	0.140	0.896	1.442
Location (β) 4d Item 13	0.513	0.007	0.119	0.291	0.761

4. Discussion

The findings of this study provide compelling evidence that video surveillance systems exert a significant psychological impact, leading to observable behavioral modifications in individuals subjected to continuous monitoring. By examining the interrelations between perceived psychological pressure, belief in active surveillance, and the perceived omnipresence of surveillance technologies, the study contributes to a systemic understanding of how surveillance environments operate as socio-technical systems that shape human behavior. These systems function through recursive feedback loops in which technological infrastructures, cognitive perceptions, and behavioral adaptations interact dynamically. The results are consistent with established theoretical frameworks, particularly Foucault's [50] concept of the Panopticon and Zuboff's [64] theory of surveillance capitalism, reinforcing the idea that the mere perception of being observed activates mechanisms of internalized control, resulting in behavioral self-regulation and conformity.

The results confirmed H1, indicating that perceived psychological pressure significantly influences behavioral modifications. The factor analysis demonstrated that individuals who experience higher levels of discomfort and heightened awareness of constant monitoring (Factor 1) are more likely to alter their actions, exhibit greater self-awareness, or suppress certain behaviors (Factor 2). This supports Foucault's panoptic self-regulation theory, which suggests that surveillance fosters a form of internalized discipline, where individuals proactively conform to perceived social expectations to avoid negative scrutiny.

Further, H2 was supported by the findings, showing that the belief in active surveillance (Item 5) heightens behavioral vigilance in surveilled spaces (Item 7). The statistically significant relationship between these variables confirms the premise of social control theory [73], which posits that individuals who believe their actions are actively monitored are more likely to engage in self-regulation. From a systems perspective, this illustrates how surveillance functions as a feedback mechanism within a broader socio-technical system, where belief in observation alone can trigger behavioral adjustments without the need for direct intervention. Similarly, Yesil [4] and Shapiro [5] emphasize that surveillance in urban spaces is designed not just to deter criminal activity but also to subtly guide and control social behavior. This finding thus highlights a key psychological pathway within surveillance systems: the perception of being observed becomes a systemic input that modifies behavioral outputs, reinforcing control through internalized awareness rather than external enforcement.

The study also found support for H3, indicating that the perceived omnipresence of surveillance technology (Item 15) significantly amplifies psychological pressure (Factor 1). This finding aligns with the literature [63,64], which suggests that advancements in surveillance technology have led to a widespread perception that monitoring is continuous and inescapable. Individuals who perceive surveillance as omnipresent experience higher levels of psychological distress, reinforcing the argument that modern technological surveillance fosters a persistent state of self-regulation. This psychological impact is further supported by McCahill and Finn [34], who argue that the normalization of surveillance in contemporary societies creates a culture of suspicion, in which individuals continuously evaluate their actions based on the possibility of being observed. The results also align

with Monahan [32], who highlights that the expansion of surveillance technology contributes to feelings of alienation and distrust, as people become increasingly aware that their movements, interactions, and decisions may be monitored and assessed.

The mediation analysis confirmed H4, demonstrating that immediate psychological pressure (Item 9) serves as an intermediary mechanism through which concerns about lifestyle monitoring (Item 13) lead to behavioral modifications (Item 10). This supports Staples's [2] assertion that surveillance-related anxiety does not always directly alter behavior but operates through intermediate emotional and cognitive responses. The study found that macro-level concerns about surveillance gradually translate into real-time psychological discomfort, which, in turn, results in behavioral self-regulation.

The statistical relationships observed in this study underscore the recursive nature of surveillance effects within socio-technical systems. The confirmation of hypotheses H1–H4 illustrates not only direct connections between psychological pressure and behavioral modification but also the more nuanced role of perceived omnipresence and belief in active monitoring. Interpreting these results through a systems lens, it becomes evident that surveillance exerts its influence not merely through formal enforcement mechanisms but by shaping the internal cognitive environments of individuals. The confirmed mediation effect (H4) highlights how abstract concerns—such as lifestyle profiling—translate into immediate emotional responses and behavioral adjustments. This pathway reflects the internalization of systemic cues, consistent with Foucault's theory of disciplinary power and with Meadows' notion of balancing feedback loops. Importantly, the results suggest that individuals are not only reacting to what surveillance does but also to what surveillance symbolizes: control, judgment, and categorization. These internalized perceptions may have far-reaching consequences, contributing to broader patterns of behavioral conformity, emotional suppression, and withdrawal from authentic or politically sensitive expression in monitored spaces. Such interpretations position the present findings within a larger societal dialogue on autonomy, algorithmic governance, and behavioral predictability.

The results derived from this study carry meaningful implications for both policy and practice, particularly when surveillance is viewed as part of an interconnected socio-technical system. The results underscore the need for regulatory frameworks that account not only for legal compliance but also for the unintended psychological and behavioral consequences that emerge from systemic interactions between surveillance technologies and human perception. While the GDPR provides essential safeguards against excessive and disproportionate monitoring, emphasizing principles such as lawfulness, purpose limitation, and data minimization, this study demonstrates that even lawful surveillance can generate psychological pressure that indirectly constrains individual autonomy. In this context, surveillance functions as a regulatory system in itself, influencing behavior through internalized norms rather than formal sanctions. The role of Data Protection Authorities (DPAs) is therefore critical: their interventions serve as external control mechanisms that can realign system behavior with fundamental rights. Cases in which organizations have been fined for intrusive video surveillance practices show that regulatory bodies acknowledge the broader systemic impact on individuals' rights and freedoms. These fines should not be viewed merely as punitive measures, but as corrective signals within a dynamic compliance system. Given the complexity of surveillance ecosystems, GDPR enforcement must integrate legal, psychological, and behavioral perspectives to ensure holistic protection of individual rights in increasingly monitored environments.

This study advances the theoretical understanding of surveillance and self-regulation by situating psychological and behavioral responses within the dynamics of complex socio-technical systems. By demonstrating that the mere perception of surveillance can activate self-censorship, the research reinforces prior work on behavioral regulation under condi-

tions of perceived observation [50,64], illustrating how internalized monitoring functions as a feedback mechanism within a broader system of social control. This systemic perspective highlights that surveillance does not operate in isolation but as part of an interactive network of technologies, norms, and individual cognition.

Furthermore, the study contributes to ongoing debates about the erosion of anonymity in public spaces, showing that widespread surveillance diminishes the capacity for individuals to navigate social environments without being subject to observation or profiling. This contributes to a systemic contraction of expressive freedom, as individuals adapt their behavior not in response to direct intervention but to the implicit conditions of monitored environments. Echoing Arendt's [31] concerns about the loss of the public realm, the findings emphasize a growing societal challenge: how to maintain a resilient equilibrium between the functional imperatives of security systems and the preservation of fundamental freedoms in democratic societies.

5. Conclusions

This study provides empirical and theoretical insights into the behavioral and psychological impacts of video surveillance, framing it as a component of a broader socio-technical system. By demonstrating that the mere perception of being monitored can lead to self-censorship and behavioral adaptation, the research supports the conceptualization of surveillance as a dynamic feedback mechanism that influences individual agency through internalized control. The statistically significant relationships between perceived psychological pressure, belief in active monitoring, and the omnipresence of surveillance technologies underscore how behavioral regulation emerges not only from formal enforcement but also from the anticipatory actions of individuals navigating surveilled environments.

These findings contribute to the growing literature that treats surveillance as a complex system involving interactions among legal norms, technological infrastructures, and psychological processes. For systems scholars, the study offers concrete evidence of how feedback loops, symbolic control, and emergent behavioral norms operate within socio-technical systems. It illustrates how subtle regulatory mechanisms, like perceived observation, can stabilize or disrupt system behavior without direct coercion. Moreover, it suggests potential leverage points (in the Meadowsian sense) where small interventions in public perception or regulatory communication could produce disproportionate systemic effects. This opens up pathways for modeling behavioral dynamics in adaptive governance systems and supports a shift in surveillance analysis from static design to evolving interaction patterns.

While the GDPR provides a uniform legal framework, the divergence in enforcement practices across Data Protection Authorities reveals systemic inconsistencies that can affect the broader social perception of privacy rights and technological governance. In regulatory terms, the study suggests that DPAs should not only consider legal compliance but should also evaluate surveillance systems in terms of their behavioral and psychological impact. This implies that the assessment of video surveillance systems must place at the center of the analysis the need to preserve the intrinsic characteristics of the human being and should not allow data controllers to create a mere appearance of legality through a strictly technical interpretation of GDPR provisions.

The findings also highlight broader societal risks associated with the erosion of the public realm, a theme articulated by Hannah Arendt [31] and revisited in light of contemporary surveillance practices. In societies where individuals fear scrutiny or judgment in public spaces, the conditions for democratic participation and civic engagement are weakened. Surveillance, when normalized and internalized, may discourage protest, dissent, or even casual acts of expression. These consequences are particularly concerning in democratic societies, where freedom of assembly and expression are foundational rights.

The challenge, therefore, lies in designing surveillance systems that uphold security and efficiency without compromising the psychological and behavioral conditions necessary for a free and open society.

Although the present research framed surveillance within a socio-technical system, further elaboration is needed to examine how the identified mechanisms relate to broader societal phenomena. For instance, surveillance-induced self-censorship may contribute to rising levels of social conformity, online disinhibition, mental health issues (e.g., anxiety or stress), or even reduced civic engagement in monitored societies. These connections, which are being increasingly discussed in the literature [10,34,81], suggest that the implications of surveillance extend far beyond the immediate act of observation, influencing democratic participation, social trust, and identity formation.

While this study provides valuable insights, it is important to acknowledge its limitations, particularly in the context of understanding surveillance as a complex socio-technical system. First, the reliance on self-reported survey data introduces potential biases, such as social desirability effects, which may influence participants' responses. Future research could adopt experimental or behavioral observation methods to more accurately capture real-time behavioral adaptations within surveilled environments, thereby enriching system-level understanding through multi-modal data sources.

Second, the sample was drawn exclusively from a university population, which may limit the generalizability of findings across broader demographic or institutional settings. To better model how surveillance systems function across varied social contexts, future studies should include diverse populations, including workplace and urban surveillance scenarios, which operate under different behavioral and normative pressures.

Third, while the study identified a clear relationship between perceived surveillance and behavioral modification, it did not account for moderating variables such as individual differences in privacy sensitivity, prior exposure to surveillance, or personality traits. Integrating such factors into future models could enhance the explanatory power of surveillance systems by recognizing human heterogeneity as a critical system variable. Finally, the growing implementation of artificial intelligence-driven surveillance—such as facial recognition and predictive analytics—adds further layers of opacity and complexity to these systems. These technologies alter the structure and perception of surveillance by introducing automated decision-making elements, which may amplify behavioral self-regulation and erode individual autonomy in new ways.

Overall, this study offers strong empirical support for the hypothesis that video surveillance exerts psychological pressure, thereby triggering self-regulatory behaviors that align with system-level feedback dynamics. The findings underscore the need for surveillance policies to consider not only legal frameworks but also psychological and behavioral consequences emerging from these socio-technical assemblages. As video monitoring becomes increasingly embedded in daily life, it is essential that policymakers, regulators, and designers of surveillance systems ensure that such technologies do not undermine fundamental human freedoms. By bridging theoretical models with empirical data, this study contributes to a growing interdisciplinary discourse on surveillance, self-censorship, and autonomy within complex digital ecosystems.

Future research should continue to examine these systems holistically, incorporating diverse populations, contextual factors, and emerging surveillance technologies such as AI-driven analytics and facial recognition. As surveillance infrastructures become increasingly embedded in daily life, maintaining a balance between public safety and individual autonomy will require interdisciplinary collaboration between technologists, legal scholars, behavioral scientists, and policymakers. The results presented here serve as a foundation for that dialogue, highlighting the need for surveillance systems that are not

only effective but also ethically and psychologically sustainable. Ultimately, understanding surveillance through a systems lens enables more adaptive, accountable, and ethically grounded governance, where technological efficiency is harmonized with the preservation of fundamental human values.

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Appendix A

Table A1. Questionnaire.

Code	Item
Item 1	In general, how interested are you in whether the space you are in is under video surveillance?
Item 2	To what extent do you know the conditions under which video surveillance cameras can be installed in a space?
Item 3	Have you ever requested information regarding the legality of installing video surveillance cameras in a specific space?
Item 4	Have you ever challenged the fact that you are being recorded by a video surveillance camera?
Item 5	Do you believe that video recordings are analyzed by those who conduct the surveillance?
Item 6	How likely do you think it is that, under normal conditions, you could be identified in a video recording?
Item 7	When entering a space that is under video surveillance, are you more attentive than usual to your gestures?
Item 8	Have there been situations where you refrained from making a gesture in a video-surveilled space for fear that it might be perceived as abnormal by those who have access to the recordings?
Item 9	Have you ever felt discomfort or pressure from being recorded while carrying out everyday activities (e.g., shopping, participating in recreational activities, etc.)?
Item 10	Do you believe that video surveillance changes the way you behave?
Item 11	In a video-surveilled space, have you ever felt the need to avoid the cameras' field of view because you did not want it to be known that you were in that space?
Item 12	In a video-surveilled space, have you ever felt the need to avoid the cameras' field of view because you did not want it to be known that you were participating in a certain activity or using a particular service?
Item 13	Have you ever felt discomfort or pressure from the possibility that, due to video surveillance, your lifestyle could be detected and analyzed?
Item 14	Would you feel safe if there were continuous video monitoring from the moment you leave your home until you return?
Item 15	To what extent do you agree with the statement: "Nowadays, everything you do is known anyway"?

References

1. Lyon, D. *Surveillance Society: Monitoring Everyday Life*; Open University Press: Buckingham, UK, 2001.
2. Staples, W.G. *Everyday Surveillance: Vigilance and Visibility in Postmodern Life*, 2nd ed.; Rowman & Littlefield: Lanham, MD, USA, 2014.
3. Lin, L.; Purnell, N. A world with a billion cameras watching you is just around the corner. *Wall Str. J.* **2019**. Available online: https://www.wsj.com/articles/a-billion-surveillance-cameras-forecast-to-be-watching-within-two-years-11575565402 (accessed on 13 May 2025).
4. Yesil, B. *Video Surveillance: Power and Privacy in Everyday Life*; LFB Scholarly Publishing: El Paso, TX, USA, 2010.

5. Shapiro, A. *Design, Control, Predict: Logistical Governance in the Smart City*; University of Minnesota Press: Minneapolis, MN, USA, 2020.
6. Lauer, J.; Lipartito, K. (Eds.) *Surveillance Capitalism in America*; University of Pennsylvania Press: Philadelphia, PA, USA, 2021.
7. Bodie, M.T. The law of employee data: Privacy, property, governance. *Ind. Law J.* **2022**, *97*, 707–748.
8. Rule, J.B. *Privacy in Peril: How We Are Sacrificing a Fundamental Right in Exchange for Security and Convenience*; Oxford University Press: Oxford, UK, 2007.
9. Macnish, K. *The Ethics of Surveillance: An Introduction*; Routledge: London, UK, 2017.
10. Monahan, T. *Crisis Vision: Race and the Cultural Production of Surveillance*; Duke University Press: Durham, NC, USA, 2022.
11. Jansen, A.M.; Giebels, E.; van Rompay, T.J.L.; Junger, M. The influence of the presentation of camera surveillance on cheating and pro-social behavior. *Front. Psychol.* **2018**, *9*, 1937. [CrossRef] [PubMed]
12. Volosevici, D. Some Considerations on Video-Surveillance and Data Protection. *Jus Civitas J. Soc. Legal Stud.* **2018**, *69*, 7–14.
13. Merrick, R.; Ryan, S. Data privacy governance in the age of GDPR. *Risk Manag.* **2019**, *66*, 38–43.
14. Aas, K.F.; Gundhus, H.O.; Lomell, H.M. *Technologies of Insecurity: The Surveillance of Everyday Life*; Routledge-Cavendish: Abingdon, UK, 2009.
15. Harding, J.M. *Performance, Transparency, and the Cultures of Surveillance*; University of Michigan Press: Ann Arbor, MI, USA, 2018.
16. Ball, K. Surveillance in the workplace: Past, present, and future. *Surveill. Soc.* **2022**, *20*, 455–472. [CrossRef]
17. European Data Protection Board (EDPB). Guidelines 3/2019 on Processing of Personal Data through Video Devices. 2019. Available online: https://edpb.europa.eu (accessed on 10 January 2025).
18. Kaplan, S. To be a face in the crowd: Surveillance, facial recognition, and a right to obscurity. In *Everyday Life in the Culture of Surveillance*; Samuelsson, L., Cocq, C., Gelfgren, S., Enbom, J., Eds.; Nordicom, University of Gothenburg: Gothenburg, Sweden, 2023; pp. 45–66. [CrossRef]
19. Reeves, J. *Citizen Spies: The Long Rise of America's Surveillance Society*; New York University Press: New York, NY, USA, 2017.
20. Norris, C.; Armstrong, G. *The Maximum Surveillance Society: The Rise of CCTV*; Berg: Oxford, UK, 1999.
21. Alfino, M.; Mayes, G.R. Reconstructing the right to privacy. *Soc. Theory Pract.* **2003**, *29*, 1–18. Available online: https://www.jstor.org/stable/23559211 (accessed on 10 March 2025).
22. Ahmad, M.A.; Baryannis, G.; Hill, R. Defining Complex Adaptive Systems: An Algorithmic Approach. *Systems* **2024**, *12*, 45. [CrossRef]
23. Sobb, T.; Moustafa, N.; Turnbull, B. Responsible Resilience in Cyber–Physical–Social Systems: A New Paradigm for Emergent Cyber Risk Modeling. *Future Internet* **2025**, *17*, 282. [CrossRef]
24. Zimmerman, B.; Lindberg, C.; Plsek, P. *A Complexity Science Primer: What Is Complexity Science and Why Should I Learn About It*; Adapted From: *Edgeware: Lessons From Complexity Science for Health Care Leaders*; VHA Inc.: Dallas, TX, USA, 1998.
25. Hempel, L.; Toepfer, E. *On the Threshold to Urban Panopticon? CCTV in European Cities and Assessing Its Social and Political Impacts*; Working Paper No. 15; TU Berlin Centre for Technology and Society Technical: Berlin, Germany, 2004.
26. Golda, T.; Guaia, D.; Wagner-Hartl, V. Perception of Risks and Usefulness of Smart Video Surveillance Systems. *Appl. Sci.* **2022**, *12*, 10435. [CrossRef]
27. Bentham, J. *Panopticon*; T. Payne: London, UK, 1791.
28. Haggerty, K.D.; Samatas, M. (Eds.) *Surveillance and Democracy*; Routledge: Abingdon, UK, 2010.
29. Cohen, J.E. *Configuring the Networked Self: Law, Code, and the Play of Everyday Practice*; Yale University Press: New Haven, CT, USA, 2012.
30. Lyon, D. *The Culture of Surveillance*; Polity Press: Cambridge, UK, 2018.
31. Arendt, H. *The Human Condition*; University of Chicago Press: Chicago, IL, USA, 1958.
32. Monahan, T. *Surveillance in the Time of Insecurity*; Rutgers University Press: New Brunswick, NJ, USA, 2010.
33. Barnard-Wills, D. *Surveillance and Identity: Discourse, Subjectivity and the State*; Ashgate: Farnham, UK, 2012.
34. McCahill, M.; Finn, R.L. *Surveillance, Capital and Resistance: Theorizing the Surveillance Subject*; Routledge: London, UK, 2014.
35. Rachels, J. Why privacy is important. *Philos. Public Aff.* **1975**, *4*, 323–333. Available online: http://www.jstor.org/stable/2265077 (accessed on 13 January 2025).
36. Vélez, C. *Privacy Is Power: Why and How You Should Take Back Control of Your Data*; Melville House: Brooklyn, NY, USA, 2021.
37. Ebert, I.; Wildhaber, I.; Adams-Prassl, J. Big data in the workplace: Privacy due diligence as a human rights-based approach to employee privacy protection. *Big Data Soc.* **2021**, *8*, 20539517211013051. [CrossRef]
38. Zwilling, M.; Klien, G.; Lesjak, D.; Wiechetek, L.; Cetin, F.; Basim, H.N. Cyber Security Awareness, Knowledge and Behavior: A Comparative Study. *J. Comput. Inf. Syst.* **2022**, *62*, 82–97. [CrossRef]
39. Schauer, F. *Fear, Risk and the First Amendment: Unraveling the Chilling Effect*; Faculty Publications, Boston University: Boston, MA, USA, 1978; Volume 879. Available online: https://scholarship.law.wm.edu/facpubs/879 (accessed on 13 January 2025).
40. Solove, D.J. A taxonomy of privacy. *Univ. Pa. Law Rev.* **2006**, *154*, 477–488. [CrossRef]
41. Solove, D.J. *Understanding Privacy*; Harvard University Press: Cambridge, MA, USA, 2008.

42. Nissenbaum, H. *Privacy in Context: Technology, Policy, and the Integrity of Social Life*; Stanford University Press: Stanford, CA, USA, 2010.
43. Marx, G.T. *Windows into the Soul: Surveillance and Society in an Age of High Technology*; University of Chicago Press: Chicago, IL, USA, 2016.
44. Von Bertalanffy, L. *General System Theory: Foundations, Development, Applications*; George Braziller: New York, NY, USA, 1968.
45. Von Bertalanffy, L. *Perspectives on General System Theory: Scientific-Philosophical Studies*; George Braziller: New York, NY, USA, 1975.
46. Meadows, D.H. *Thinking in Systems: A Primer*; Wright, D., Ed.; Chelsea Green Publishing: White River Junction, VT, USA, 2008.
47. Luhmann, N. *Social Systems*; Stanford University Press: Stanford, CA, USA, 1995.
48. Luhmann, N. *Introduction to Systems Theory*; Barrett, P., Ed.; Polity Press: Cambridge, UK, 2013.
49. Moeller, H.G. *Luhmann Explained: From Souls to Systems*; Open Court: Chicago, IL, USA, 2006.
50. Foucault, M. *Discipline and Punish: The Birth of the Prison*; Sheridan, A., Translator; Pantheon Books: New York, NY, USA, 1977.
51. Jackson, M. *Critical Systems Thinking and the Management of Complexity*; John Wiley & Sons: New York, NY, USA, 2019.
52. Maturana, H.R.; Varela, F.J. *The Tree of Knowledge: The Biological Roots of Human Understanding*, 2nd ed.; Shambhala Publications: Boulder, CO, USA, 1992.
53. Alvarez, J.T.; Ramírez Correa, P. Brief Review of Systems, Cybernetics, and Complexity. *Complexity* **2023**, *2023*, 8205320. [CrossRef]
54. Kumar, S.; Bhowmik, B. Emergence, Evolution, and Applications of Cyber-Physical Systems in Smart Society. In Proceedings of the 2024 Fourth International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT), Bhilai, India, 11–12 January 2024; pp. 1–8.
55. European Parliament. General Data Protection Regulation (Regulation (EU) 2016/679). 2016. Available online: https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32016R0679&from=EN (accessed on 13 January 2025).
56. Ogriseg, C. GDPR and Personal Data Protection in the Employment Context. *Labour Law Issues* **2017**, *3*, 1–24. [CrossRef]
57. Kuner, C.; Bygrave, L.A.; Docksey, C.; Drechsler, L.; Tosoni, L. *The EU General Data Protection Regulation: A Commentary/Update of Selected Articles*; SSRN: Rochester, NY, USA, 2021. [CrossRef]
58. Won, H.-M.; Lee, H.; Song, G.; Kim, Y.; Kwak, N. Reliable Data Collection Methodology for Face Recognition in Preschool Children. *Sensors* **2022**, *22*, 5842. [CrossRef] [PubMed]
59. Der Landesbeauftragte für den Datenschutz Niedersachsen. LfD Niedersachsen Verhängt Bußgeld Über 10,4 Millionen Euro Gegen Notebooksbilliger.de. 2021. Available online: https://www.lfd.niedersachsen.de/startseite/infothek/presseinformationen/lfd-niedersachsen-verhangt-bussgeld-uber-10-4-millionen-euro-gegen-notebooksbilliger-de-196019.html (accessed on 7 February 2025).
60. Kamarinou, D.; Van Alsenoy, B. Data protection law in the EU: Roles, responsibilities, and liability. *Int. Data Priv. Law* **2020**, *10*, 395–398. [CrossRef]
61. de Hert, P.; Papakonstantinou, V. The new general data protection regulation: Still a sound system for the protection of individuals. *Comput. Law Secur. Rev.* **2016**, *32*, 179–194. [CrossRef]
62. Nissenbaum, H. Protecting privacy in an information age: The problem of privacy in public. *Law Philos.* **1998**, *17*, 559–596. Available online: https://www.jstor.org/stable/3505189 (accessed on 13 January 2025).
63. Lyon, D. *Surveillance Studies: An Overview*; Polity Press: Cambridge, UK, 2007.
64. Zuboff, S. *The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power*; PublicAffairs: New York, NY, USA, 2019.
65. Zhang, D.; Boerman, S.C.; Hendriks, H.; Araujo, T.; Voorveld, H. A Peek into Individuals' Perceptions of Surveillance. In *Advances in Advertising Research (Vol. XII)*; Vignolles, A., Waiguny, M.K., Eds.; European Advertising Academy, Springer Gabler: Wiesbaden, Germany, 2023; pp. 163–178. [CrossRef]
66. Lyon, D. Surveillance Capitalism, Surveillance Culture and Data Politics. In *Data Politics*, 1st ed.; Bigo, D., Isin, E., Ruppert, E., Eds.; Routledge: London, UK, 2019; pp. 64–77. [CrossRef]
67. Lankton, N.; McKnight, D.; Tripp, J. Technology, Humanness, and Trust: Rethinking Trust in Technology. *J. Assoc. Inf. Syst.* **2015**, *16*, 880–918. [CrossRef]
68. Westin, A. *Privacy and Freedom*; Atheneum: New York, NY, USA, 1967.
69. Manokha, I. Surveillance, Panopticism, and Self-Discipline in the Digital Age. *Surveill. Soc.* **2018**, *16*, 219–237. Available online: https://ojs.library.queensu.ca/index.php/surveillance-and-society/index (accessed on 22 April 2025). [CrossRef]
70. Segijn, C.M.; Opree, S.J.; van Ooijen, I. The Validation of the Perceived Surveillance Scale. *Cyberpsychol. J. Psychosoc. Res. Cyberspace* **2022**, *16*, 9. [CrossRef]
71. Dencik, L.; Cable, J. Digital Citizenship and Surveillance: The Advent of Surveillance Realism—Public Opinion and Activist Responses to the Snowden Leaks. *Int. J. Commun.* **2017**, *11*, 763–781.
72. Augusto, F.R.; Simões, M.J. To See and Be Seen, to Know and Be Known: Perceptions and Prevention Strategies on Facebook Surveillance. *Soc. Sci. Inf.* **2017**, *56*, 596–618. [CrossRef]
73. Marx, G.T. What's new about the "new surveillance"? Classifying for change and continuity. *Surveill. Soc.* **2002**, *1*, 9–29. [CrossRef]

74. Henschke, A. *Ethics in an Age of Surveillance: Personal Information and Virtual Identities*; Cambridge University Press: Cambridge, UK, 2017. [CrossRef]
75. Ozili, P.K. The Acceptable R-Square in Empirical Modelling for Social Science Research. In *Social Research Methodology and Publishing Results: A Guide to Non-Native English Speakers*; IGI Global: Hershey, PA, USA, 2023; pp. 134–143.
76. Bornewasser, M.; Kober, M. Videoüberwachung: Kriminalitätsreduzierung und gezielte Verdrängung. Bericht über eine Evaluationsmaßnahme in der Stadt Luxemburg [Video Surveillance: Crime Reduction and Targeted Displacement. Report on an Evaluation Measure in the City of Luxembourg]. *Forum Krim.* **2012**, *2*, 34–42.
77. Bornewasser, M.; Schulz, F. Videoüberwachung öffentlicher Straßen und Plätze, Ergebnisse eines Pilotprojektes in Brandenburg. Ergebnisse der Evaluationsstudie im Land Brandenburg [Video Surveillance of Public Roads and Squares, Results of a Pilot Project in Brandenburg. Results of the Evaluation Study in the State of Brandenburg]. In *Ergebnisse der Evaluationsstudie im Land Brandenburg*; Bornewasser, M., Classen, C.D., Stolpe, I., Eds.; Verlag für Polizeiwissenschaft: Frankfurt am Main, Germany, 2008.
78. Podsakoff, P.M.; MacKenzie, S.B.; Lee, J.Y.; Podsakoff, N.P. Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. *J. Appl. Psychol.* **2003**, *88*, 879–903. [CrossRef] [PubMed]
79. Hu, L.T.; Bentler, P.M. Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria versus New Alternatives. *Struct. Equ. Model.* **1999**, *6*, 1–55. [CrossRef]
80. Hayes, A.F. *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach*, 3rd ed.; The Guilford Press: New York, NY, USA, 2022.
81. Mori, Y.; Tiiri, E.; Khanal, P.; Khakurel, J.; Mishina, K.; Sourander, A. Feeling Unsafe at School and Associated Mental Health Difficulties among Children and Adolescents: A Systematic Review. *Children* **2021**, *8*, 232. [CrossRef] [PubMed]

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