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Trust and Social Control in Domesticating Smart Technologies:

Understanding Smart Technology Use Among Students in Poland and the UK

Abstract: Smart technologies have become an integral part of everyday life, creating the need for a better understanding of how they are used across diverse sociocultural contexts and social groups. We draw on data from a representative survey (2023–2024) of 2,098 students in Poland and the UK to explore differences in smart technology use. Students in the UK are significantly more likely to use smart technologies than their peers in Poland. Regression analysis shows higher usage among men, and among individuals with greater trust in AI, better English skills, a stronger sense of social pressure, and belief in human responsibility for AI. Trust and perceived social control emerge as the strongest predictors. We argue that classic domestication theory should be revised to include transparency, accountability, and social legitimacy as key conditions for integrating smart technologies into students' lives.

Keywords: domestication theory, smart technologies, social control, university students, trust in technologies.

Introduction

With the increasing digitalization of everyday life, smart technologies, including smart home solutions, voice assistants, recommendation systems, and telemedicine, are becoming increasingly integrated into home and personal practices. These are no longer tools of the future, but elements of modern infrastructure that are redefining daily rituals, social relationships, and ways of organizing life and even of managing one's own space.

Research to date shows that the development of digital technologies—including IoT, artificial intelligence (AI), and immersive tools such as virtual and augmented reality (VR/AR)—is profoundly transforming everyday life. These innovations enable the personalization of services and the automation of domestic activities. They promise increased efficiency, convenience, and responsiveness (de Souza et al. 2023; Mao & Chang 2023). E-health technologies, including those using VR/AR, are changing the way healthcare is delivered, improving diagnosis and patient care (Sharma & Chamoli 2024).

AI and IoT can support safety and productivity; for instance, they may help older workers cope with declining fitness (Abril-Jimenez et al. 2022).

However, the ongoing digital transformation of our everyday life is not without significant risks and challenges. The widespread integration of smart devices and AI systems raises concerns about surveillance, data privacy, and the amplification of social and global inequalities (Adams 2025; Kołodziejska & Paliński 2025; Zuboff 2023). IoT and wearable technologies often operate in ways that are difficult for users to understand fully or control, and this may lead to potential violations of personal autonomy and informational security (Fúster et al. 2024).

Despite the growing body of research on smart technologies, an in-depth analysis of the sociocultural determinants of their everyday familiarization, especially among young adults, is still lacking. Much of the literature to date has focused on the functional (Ford et al. 2017), technical (Mocrii et al. 2018), or economic aspects (Cvitić et al. 2021) of innovation implementation. The role of trust, social control, and normative notions of responsibility—which are increasingly proving important for integrating these solutions in everyday life—have not been fully considered. Particularly little is known about how the taming of technology occurs in different geographical or cultural contexts, where levels of digitalization, institutional support, and lifestyles differ significantly.

This research gap not only has repercussions for theory but is also highly relevant in designing and implementing technology. For both social research and technology, it seems important to understand how smart technologies become embedded in everyday life not merely as tools but as socially and emotionally charged artifacts. Existing models of technology adaptation, such as TAM (Davis et al. 2024) or UTAUT (Akinnuwesi et al. 2022), focus on the functional rationale of user decisions, while neglecting sociodemographic, emotional, and normative-cognitive aspects that may also influence the integration of technology. Specifically, as smart technologies—ranging from home monitoring systems and cleaning robots to biometric wearables and AI-driven health tools—become more pervasive, they raise complex ethical questions of trust and responsibility (Gordon 2025). These technologies often operate in opaque ways. They map private spaces and collect sensitive data, which can erode user trust and exacerbate digital vulnerability.

Exploring what factors predispose individuals to integrate smart technologies into their lives is important not only for the development of theory but also for practice, especially in the design of inclusive, ethical, and socially acceptable solutions based on new technologies, including AI. This requires moving beyond technical efficiency and functionality to consider emotional and normative-cognitive aspects of technology use within specific sociocultural contexts.

Our research addresses a critical empirical and theoretical gap in understanding cross-cultural differences in smart technology use (including AI) of university students in the UK and in Poland. The question is particularly relevant given the rapid uptake of generative AI technologies in higher education. Recent research has shown that cultural and social norms significantly influence students' attitudes toward the adoption of AI (Ma et al. 2024; Ursavaş et al. 2025). For example, Ma et al. (2024) demonstrate that cultural background affects behavioral intentions in regard to AI in learning environments, while Ursavaş et al. (2025) emphasize the role of social norms and self-efficacy in the adoption of generative AI by students in higher education. These studies underscore the importance of considering cultural context when examining how students domesticate technology.

We draw on representative samples of university students in Poland and the UK to enhance our understanding of how cultural and educational contexts, among other factors, may influence students' engagement with smart technology. Our study contributes to sociological and technology-adaptation research by identifying factors that explain the different frequency with which students in Poland and the UK use smart technology in everyday life. To this end, we adopted an exploratory research design and drew on the theory of technology domestication (Hector & Strüver 2025; Silverstone & Haddon 1996). We extended the theory to explore not only the relationship between technology and classic sociodemographic characteristics (such as age, gender, and place of origin), but also emotional components (e.g., trust in AI) and normative-cognitive components (e.g., attribution of moral and legal responsibility for AI's actions, and perceived social control). To assess the degree to which these technologies are "tamed" in users' daily practices, we introduce the Smart Technology Frequency Scale, which we developed for this purpose.

This study brings a new perspective to research on technology adaptation by extending domestication theory to include emotional and normative-cognitive components, which we argue may be particularly important for the domestication of AI-based smart technologies. Specifically, our study introduces novel variables related to AI ethics, such as the attribution of responsibility for AI actions (moral, legal, engineering, algorithmic) and perceived social control, into the predictive model. Thus, it redefines domestication not only as the spatial taming of technologies (Sorensen 2006) but also as socially negotiated consent to their presence and action.

Framework

As an interpretive framework, this study uses technology domestication theory (Silverstone & Haddon 1996), which provides tools for understanding the social familiarization of technology in everyday life. Unlike models based on the assumption of rational choice (such as TAM or UTAUT), domestication theory assumes that technology is not integrated into everyday life solely based on its utility. On the contrary, it becomes part of daily life through its gradual inscription into rituals, social relationships, norms, and personal identity (Lee et al. 2017). In this view, technologies function not merely as tools but as co-creators of everyday social space (Pink et al. 2022; Strengers 2022; Strengers & Kennedy 2020).

In the classical view, the domestication of technology proceeds in four stages. These illustrate how technology becomes domesticated and embedded in everyday life (Silverstone & Haddon 1996). The appropriation phase refers to the moment when the technology is acquired and given meaning. In other words, it refers to who acquires it and for what reasons (e.g., "for the safety of children," "because everyone already has it," "to make it more convenient"). Objectification (embedding) is the process of physically and symbolically locating the technology in the domestic or social space: where and how it is domesticated, where it is placed, how it is displayed, who has access to it, and what it looks like in practice. In the incorporation phase, technology becomes embedded in the rituals and habits of everyday life. It becomes an integral part of a daily routine, for instance, to check health parameters, open the door of one's home with an app, or communicate with a child via camera. Conversion, on the other hand, refers to the point at which the technology acquires and reflects the identity of the household and its members (Siles 2023). In this phase, the user demonstrates its presence to others, giving it a representational function ("with us everything works intelligently"). Domestication, therefore, does not end with the purchase; on the contrary, it is an ongoing process, negotiated through time, space, and social relations.

In Poland, a cross-sectional survey was conducted using respondent-driven sampling (RDS) (Kozak & Fel 2024; Phukan & Hazarika 2024), which is a method "designed to generate estimates that are representative of the wider population of interest, despite biased sampling" (White et al. 2012: 397). The Savanta Research Panel (n > 150,000 university students) was used in the UK (Brainard et al. 2023). To ensure representativeness, the panel's respondents in the UK were recruited using the Universities and Colleges Admissions Service (UCAC) database (Neves & Sephenson 2023). To obtain a representative sample of respondents from Poland, we used limits based on the ISCED-F 2013 classification of fields of study published by the Polish Statistical Office (GUS 2023). A sample of students from the UK (N = 1010) and Poland (N = 1088) were surveyed using quantitative sociological research between 2023 and 2024. The data were analyzed using SPSS v.29.

Students were selected as the primary focus of the project due to their specific characteristics in regard to social group and use of technology. Below is a presentation of the social and demographic characteristics of the sample. The average age of the students was 22.85 years (SD = 7.7).

These students belong to the generation of digital natives—people who have grown up in a digital environment and treat technology as a natural part of everyday life. Technology shapes their social relationships, education, communication, and identity (Prensky 2009; Vergara et al. 2025). Their relationship with AI is not only utilitarian but also anticipatory. As future professionals and policy makers, students anticipate the directions of social and normative change (Mishra et al. 2024). Research indicates that in their technological practices they link their educational sphere with their private use of AI tools (Crompton & Burke 2023) and that high digital proficiency translates into self-efficacy and reflexivity in the use of technology (Tóth et al. 2022). Universities are thus not only a place for socialization but also for the formation of innovative competences and digital citizenship (Wang, Lu et al. 2025).

The inclusion of students from Poland and the UK enabled us to make a comparative analysis of attitudes towards AI in two distinct institutional and cultural contexts. While both countries are part of a shared European context, they differ in the extent to which technology is integrated in education and the level of institutional support for digitization (Mićić 2017; Pargman & McGrath 2021). In the UK, AI tools are embedded in university policies and didactics (Pérez-Paredes 2022). In contrast, Poland's adoption of AI tools has tended to be more bottom-up, characterized by limited infrastructure and lower systemic pressure (Mahmud et al. 2019). These differences reflect broader disparities in levels of innovation and in educational systems (Dabic et al. 2016). The disparities encompass both formal structures and cultural pathways for adopting new technological solutions. Therefore, a comparison of the two countries provides insight not only into students' attitudes toward new technologies but also into how the digital transformation of academia supports the domestication of new technologies.

To be able to measure the intensity of use of smart and AI-based technologies in everyday life, we developed a Smart Technology Frequency Scale. This scale was constructed based on seven questionnaire items (as part of a broader study of Polish and UK students' attitudes towards AI, n = 2028) that cover a variety of uses of modern technology relevant to current debates on "digital domesticity" (Hernan & Ramirez-Figueroa 2021). The operationalization of the dependent variable is in line with the broad concept of living with smart technologies, as discussed in the literature (Maalsen 2020).

The scale includes two complementary dimensions: home and embedded technologies (e.g., biometrics, health monitoring, smart home solutions) and mobile and personal technologies (location-based apps, voice assistants, recommendation systems, telemedicine). Such a division reflects the contemporary understanding of the home as not only a physical space but also as a digital and distributed space in which the boundaries between the private and the public are blurred (Strengers & Nicholls 2018). The technological elements included in the scale are representative examples of tools that are simultaneously widely used, highly personalized, and intensely embedded in everyday rituals—from locating objects and moving around, to managing health and safety, to consuming content and interacting with algorithms.

The summary index was constructed by summing the scores across seven variables (7–35), each measured on a uniform five-point frequency scale to ensure internal consistency. Preliminary analysis indicated good reliability of the scale ($\alpha > 0.729$) and supported the validity of treating it as a unidimensional indicator.

The study was based on Student's t-test, robust ANOVA and linear regression tests (using IBM SSPSS v. 29.0.1.1 and jamovi v. 2.6.44.0 with the Walrus extension). First, we performed Student's t-test to explore cross-national differences. Then, we drew on robust ANOVA and post hoc analysis to explore further differences in the frequency of smart technology use between student groups for the interaction between the place of study and the field of study. Finally, we performed linear regression tests to have a more holistic overview of factors predicting the frequency of smart technology use. For this, we used three sets of independent variables corresponding to three aspects: (1) sociodemographic characteristics, (2) the emotional component, and (3) the normative-cognitive component related to the attribution of responsibility for AI actions.

Results

A comparison of mean scores on the Smart Technology Frequency Scale between students in Poland and in the UK revealed statistically significant differences. The mean for students in Poland was 18.92 ($SD = 5.23$), while the mean for students in the UK was 21.41 ($SD = 4.81$). The difference in means was −2.49 points, indicating a significantly lower level of smart technology use in the Polish group ($p < .001$, two-sided test).

Levene's test showed that the variances in the two groups differed significantly ($F = 8.194$, $p = .004$), so a variant of the t-test without the assumption of equality of variances was adopted in the further analysis. The result of the t-test was highly significant: $t = -11.351$, $df \approx 2096$, $p < .001$. In addition, all three effect coefficients (Cohen's d, Hedges' correction, Glass' delta) were approximately −0.49, indicating a moderate effect (mean effect size). The 95.0% confidence interval for the difference in means does not include zero (−2.92; −2.06). This further confirms the significance of the differences.

Robust ANOVA analysis (Welch ANOVA) showed statistically significant differences in the frequency of smart technology use between groups defined by the interaction of place of study and field of study ($F(7, 176) = 21.30$, $p < .001$). The effect size was moderate ($ES = 0.34$) and the bootstrap-estimated confidence interval ($CI = 0.21–0.47$) confirmed the stability of the effect.

Post hoc analysis (Games-Howell) showed that students in the UK, particularly those studying social-humanities (UK–SSH), were significantly more likely to use smart technology than all comparison groups of students in Poland (science—STEM, social-humanities—SSH, health and medical sciences—HSM; other—Oth). The differences were statistically significant ($p < .001$), and the mean scores of the Polish groups were lower by between 2.03 and 3.20 points, corresponding to approximately 6.0%–9.0% of the total scale (range: 7–35). In addition, all the Polish student groups had significantly lower scores than the UK–STEM and UK–HSM students. The differences ranged from 2.04 to 3.22 points, which is also about 6.0%–9.0% of the total scale ($p < .05$) (Tab. 1).

Table 1

Post hoc comparisons (Games-Howell) for the interaction of country and field of study relative to frequency of smart technology use

	95% Confidence Interval		p		Lower	Upper
		psi-hat				
UK-SSH	PL-STEM	3.145	<.001		2.072	4.217
	PL-Oth	3.203	<.001		1.111	5.294
	PL-SSSH	2.619	<.001		1.611	3.626
	PL-HSM	2.027		.01	0.243	3.810
PL-STEM	UK-STEM	−3.023	<.001		−4.390	−1.657
	UK-HSM	−3.160	<.001		−4.565	−1.755
PL-Oth	UK-STEM	−3.081	<.001		−5.318	−0.844
	UK-HSM	−3.218	<.001		−5.477	−0.959
PL-SSH	UK-STEM	−2.497	<.001		−3.813	−1.181
	UK-HSM	−2.635	<.001		−3.991	−1.278
PL-HSM	UK-HSM	−2.042		.03	−4.031	−0.054

Only statistically significant differences (< .05) were included in the table.

According to domestication theory, technology is not integrated into everyday life solely based on its utility. Rather, it becomes part of life through its gradual inscription into rituals, social relations, and individual identity (Sovacool & Hess 2017). We do not treat this theory as a closed explanatory model but rather as a framework that opens up new avenues for exploring attitudes toward new technologies. Recent literature increasingly highlights the importance of emotions (Fel & Kozak 2025), differences in worldview (Vaughan et al. 2025), and the attribution of responsibility (Candela et al. 2023) as key factors influencing attitudes to algorithmic systems. Therefore, the regression model employed a tripartite categorization of independent variables, corresponding to three complementary dimensions: (1) sociodemographic characteristics, (2) the emotional component, and (3) the normative-cognitive component, specifically related to the attribution of responsibility for AI actions.

The first set of variables included the classic sociodemographic characteristics that often serve as contextual variables in research on technology use. These included age, gender, size of locality of origin, assessment of English language proficiency, assessment of family financial situation, and declared academic performance. English language proficiency was included as a specific indicator of cultural capital that is relevant for independently navigating the new technological environment (Wu & Wang 2025). Age and place of origin reflect well-documented variables in the literature in terms of digital competence, lifestyle patterns, and degree of integration into smart technology infrastructure (Cowie et al. 2020; Shin et al. 2021).

The second group of variables was related to the emotional component of an individual's relationship with AI. A key variable was the level of trust in new technologies, understood as emotional openness or acceptance of a technology that can operate autonomously, beyond direct human control (Fel & Kozak 2025). Trust has long been recognized as a critical determinant of technology acceptance, influencing user engagement, perceived safety, and willingness to delegate decision-making to heteroscedastic systems (Afroogh et al. 2024; Gulati et al. 2024). In addition, two further indicators were included: feelings of guilt and ambivalence associated with using AI, and belief in one's own agency in using it. These variables capture emotional-reflective attitudes towards technology, including feelings of control, autonomy, or moral discomfort that may accompany the use of intelligent systems.

The third group of variables included a normative-cognitive component, focusing on moral and social beliefs regarding responsibility for AI actions and perceptions of social control. Social control, which is often conceptualized as the influence of norms and the expectations of one's social environment, has been widely studied in research on technology adoption (Graf-Vlachy et al. 2018; Ursavaş et al. 2025). In our study, the indicator of perceived social control captured the belief that technological decisions are shaped in the context of an individual's relationship with the environment. The remaining variables referred to a hypothetical accident scenario involving an autonomous vehicle. Respondents were asked who they thought was responsible for the accident: the vehicle owner (legal responsibility), the passenger (moral responsibility), the manufacturer (engineering responsibility), or the AI itself (algorithmic responsibility). These variables aimed to capture how responsibility is attributed in a technological environment—one that inherently challenges traditional categories of fault and causation (Aguiar et al. 2022).

The regression analysis was carried out using a hierarchical method, with nine steps of variable entry, which allowed us to follow a stepwise increase in explained variance. The final model (ninth) contained nine predictors and explained 23% of the variance in the dependent variable ($R^2 = .230$, adjusted $R^2 = .226$). The model was statistically significant ($F(9, 1695) = 56.267$, $p < .001$), and each added predictor improved its fit.

Fulfilment of the regression assumptions was confirmed at several levels. The histogram of residuals and the P-P plot indicated that the distribution of residuals was consistent with a normal distribution. The scatter plot of standardized residuals against predicted values did not reveal signs of heteroscedasticity or non-linearity. The Durbin-Watson statistic (1.875) confirmed the absence of autocorrelation. Collinearity indices (VIF < 1.25, tolerance > 0.80) and the analysis of variance ratio diagnostics did not reveal significant collinearity problems.

Regression analysis revealed that the frequency with which the students used intelligent technologies increased in the case of their being men, and with the level of their trust in AI, the intensity of their perception of social control over new technologies, their (self-assessed) English language proficiency, their attribution of moral responsibility to passengers in the context of a car operated by AI, their belief that responsible use of AI is possible, the size of their locality of origin, and their attribution of legal responsibility to the owner of the autonomous vehicle. Conversely, the frequency decreased with the respondent's age (Tab. 2).

Table 2

Factors explaining frequency of smart technology use—linear regression model

Model	Scale		UC		Beta	t	p	95% CI		Collinearity	
			B	SE				L	U	Tolerance	VIF
Trust in AI	7–35	↑	0.23	0.02	0.30	12.63	<.001	0.19	.027	0.81	1.24
Social control of AI use (family, frends, lecturers)	1–5	↑	0.57	0.09	0.15	6.14	<.001	0.39	0.75	0.81	1.23
Knowledge of English	1–5	↑	0.43	0.11	0.09	4.10	<.001	0.22	0.64	0.91	1.10
Moral responsibility for AI (car passengers)	1–5	↑	0.39	0.09	0.10	4.24	<.001	0.21	0.57	0.84	1.19
Age	—	↓	−0.06	0.02	−0.08	−3.89	<.001	−0.09	−0.03	0.97	1.03
Personal conviction about responsible use of AI	1–5	↑	0.31	0.10	0.07	3.19	0.001	0.12	0.49	0.94	1.06
Size of the place of origin	1–5	↑	0.28	0.10	0.06	2.87	0.004	0.09	0.46	0.93	1.08
Gender	F=0 M=1	↑	0.61	0.23	0.06	2.60	0.009	0.15	1.07	0.97	1.03
Legal liability for AI (car owner)	—	↑	0.17	0.09	0.05	2.00	0.046	0.00	0.34	0.87	1.15

Only statistically significant predictors were included in the model (< .05).

Discussion

Our analysis revealed that, statistically, students in the UK are significantly more likely to use smart technologies than those studying in Poland. In the UK, there is a clearly institutionalized approach to digitization. Universities having integrated digital technologies into teaching, administration, and academic communication for many years (Bar et al. 2016). This strong institutionalization of technology is evident across UK universities (Imran & Almusharraf 2025). Domestication is thus supported by the infrastructure of everyday life (Pink et al. 2022), creating conditions for the taming of other, non-work-related technologies in a systemic rather than purely individual manner. Functioning within such an environment seems to foster the transfer of technological practices to other areas of life, making users, such as university students, more confident and open to adopting similar solutions in private spaces as well.

In contrast, the adaptation of new technologies in Poland is often bottom-up, fragmented (Herbst & Wojciuk 2017), and regionally differentiated (Lorencowicz et al. 2014). As a result, the domestication cycle may remain incomplete, often halting at the initial stages of appropriation or objectification. While technology is present, it is not always culturally legitimized as the default mode of organizing daily life. Within Polish academic settings, students tend to use technology instrumentally, for learning, communication, and information acquisition (Florjančič & Wiechetek 2019), but less frequently as a tool for self-regulation, managing domestic space, or supporting mental and physical health. Consequently, as smart technologies face greater barriers to acceptance in Poland, they appear not to be anchored yet in students' everyday social practices.

Differences in familiarization with technology extend beyond the place of study. Our analysis also revealed significant differences within the educational systems themselves, particularly between students in different fields of study, as confirmed by the results of the ANOVA analysis. While the more frequent use of smart technologies by UK–STEM students aligns with expected patterns linking technological competence to digital practices, it is particularly noteworthy that UK–SSH and UK–HSM students also demonstrate a high level of sophistication in using smart technologies, surpassing even STEM students in Poland.

This observation may be explained by two overlapping factors. First, the system of higher education in the UK promotes interdisciplinarity, enabling the integration of technologies with social and ethical reflection, even within the social sciences and humanities (Yang et al. 2025). Second, the UK's liberal welfare regime is characterized by greater regulatory flexibility and trust in innovation, which facilitates experimentation with technologies in real-world settings prior to formal regulation (Bamford et al. 2024). In contrast, Poland's hybrid model, which combines a significant role for the state with individual responsibility for one's own affairs, often imposes technological, legal, or cultural constraints on technological innovation. Even within a STEM environment, students in Poland may be hesitant to adopt new technologies due to concerns about the potential legal consequences arising from unclear regulations (Miszczyński & Klimek 2023). These attitudes are consistent with findings on preferences in regard to oversight of technology in both countries. Students in the UK are more likely to favor decentralized models, while students in Poland tend to prefer state-led and formal regulatory approaches (Fel et al. 2025).

Therefore, we argue that how university students use smart technologies reflects not only their digital competence but also the broader institutional and cultural logics that shape technology integration. Among UK–SSH and UK–HSM students, smart technologies appear to be more than just tools. They seem to be part of the available technological infrastructure (appropriation) and to be imbued with social meaning and function (objectification). These technologies are actively integrated into everyday practices (incorporation) and externally communicated as symbols of modern lifestyles and personal agency (conversion). Their embeddedness in social life reinforces their institutional legitimacy, facilitating their sustained domestication to the point where they become integral to identity performance (Turkle 2005).

A different pattern emerged among university students in Poland, including those in STEM fields. Despite their high level of knowledge and engineering competence, these students remained more cautious in their everyday use of smart technologies. Their hesitancy may stem from institutional barriers, regulatory ambiguity, and limited social acceptance for technological experimentation. While these factors may have historically hindered the social legitimacy of smart technologies (as safe, acceptable, and beneficial) in Poland, recent developments suggest a shift. The rapid availability of generative AI technologies, exemplified by ChatGPT, has prompted several leading Polish universities to adopt AI-related policies and guidelines for responsible use in teaching and research (see, e.g., AMU 2024). These initiatives reflect a growing institutional effort to address the ethical, pedagogical, and governance challenges that generative AI has brought to higher education in Poland.

Although our interpretation emphasizes institutional and cultural factors in explaining the different patterns between students in various fields of study, it is important to acknowledge that alternative explanations may exist. For instance, research shows that students in the social sciences and humanities often approach technology with heightened critical awareness and may have concerns about privacy, surveillance, and ethical implications (Kumi-Yeboah et al. 2023; Wang, Li et al. 2025). Such critical engagement could influence adoption practices, suggesting that differences in use may stem not only from competence or institutional factors but also from deliberate and normative considerations.

A comparative analysis between countries (PL versus the UK) and the interaction between a student's country of study and field of study revealed significant differences in the use of smart technologies. However, these differences did not capture the full picture. To identify universal mechanisms that either support or inhibit the domestication of technology, a holistic approach, independent of place of study, was necessary. The regression analysis therefore considered all observations (PL and the UK) together to capture cross-local factors.

The analysis showed that the strongest predictors of increased use of smart technologies were trust in AI and perceptions of social control. This suggests that while users value convenience and usability (Doja et al. 2023), their acceptance of smart technologies is increasingly affected by social legitimacy—specifically control and trust. This includes the transparency of data practices, which is understood here as alignment with the norms and values of the user's social environment.

The case of higher education in the UK illustrates this dynamic well, as the institutional penalties for inappropriate use of AI are rapidly growing (McNamee 2025). Transnationally, regulatory efforts appear to focus less on individual users and more on the functioning of technological systems, particularly in terms of algorithmic transparency, accountability, and compliance with implementation standards. The overarching goal seems to be to ensure that these technologies operate within environments that foster innovation while safeguarding security, transparency, and social acceptability.

Our research also shows that students prefer predictable and recognizable external oversight mechanisms (both institutional, e.g. lecturers, and social, e.g. parents, friends) that support rather than constrain innovation. This form of control, when combined with transparency and social legitimacy, becomes essential to integrating technology into everyday life. Importantly, control and trust should not be interpreted as surveillance of the user *per se*, but rather as control of a symbiotic relationship in which users delegate part of their agency to technology. The structure of this relationship—defined by accountability, transparency, and social legitimacy—is a crucial condition for advancing through the phases of the domestication process. In this sense, technology evolves from a mere tool into a partner in a social relationship and requires trust on the same level as in human relationships (Turkle 2005).

Our results also suggest that moral responsibility significantly impacts acceptance of technology, indicating the role of users as stakeholders in the responsible use of smart technology. Legal responsibility also influences the domestication process, though to a lesser extent. Thus, we argue that clear accountability can enhance trust and satisfaction in the context of smart technologies (Shin 2021), especially when users experience positive emotions and perceive safeguards against potential errors or failures (Gursoy et al. 2019). Thus, incorporating accountability into the domestication model allows for a more nuanced understanding of how users perceive and adopt new technologies. The need for clear principles of accountability is particularly relevant given the rapid proliferation of AI technologies and the risks perceived to be associated with them. Students, like other users, seem to want clarity about who is responsible when technology malfunctions. This clarity fosters trust and a sense of safety, whereas opacity in decision-making processes can undermine confidence in the use of smart technology.

As new technologies evolve rapidly, contemporary society—often described as a "risk society" (Beck 2009)—emphasizes the importance of establishing clear accountability principles for innovation (Owen et al. 2013) as a way to mitigate the risks of the late modern era (Giddens 2023). Transparency in accountability is fundamental for users to trust new technologies and feel safe using them (Felzmann et al. 2019). The development of new technologies that transcend traditional barriers of time and space is also reshaping how individuals experience reality (Hutton & Giddens 2012). This technological transformation may lead to significant changes in sociocultural structures and influence how communities adapt to and interpret a technologically enriched reality. It may also reshape everyday interactions and decision-making processes, contributing to the emergence of new forms of social co-responsibility (Bauman 1998). Understanding these transformations may be crucial to the successful integration of innovations into modern society and to ensuring that new technologies are adopted in ways that align with social values and norms.

Conclusions and Limitations

The results of this study support shifting away from purely functional models of adapting technology toward an approach grounded in domestication theory. Such an approach should be expanded to incorporate dimensions of social legitimacy, defined by trust and control. Our study provides empirical evidence that trust and perceived control are critical factors for students in Poland and the UK in the sustainable integration of smart technologies into everyday life. These factors may be particularly important in the case of AI technologies. We therefore propose extending classic domestication theory to include such dimensions of social legitimacy. Without these elements, smart technologies may remain peripheral to everyday life—experienced as alien, temporary, or contingent.

This study has several limitations that should be acknowledged, as they also suggest directions for future research. First, our analyses are based only on data from two European countries. While Poland and the UK differ in terms of welfare regimes and levels of technology integration, they do not represent the full diversity of European or global contexts. Second, our quantitative approach to measuring "smart technology use" has limited our ability to capture the subjective meanings, motivations, and everyday practices of students in this respect. Third, although we considered a wide range of sociodemographic, emotional, and normative-cognitive factors, we did not include economic factors, local technological infrastructure, or the presence of technology in the media—all of which may influence how smart technologies are integrated into everyday life. Future research could seek to expand the scope to more countries or social groups and include qualitative methods and macro-level factors to validate and deepen our results. Fourth, although this study does not differentiate between specific types of smart technologies, we acknowledge that domestication processes may vary considerably depending on their specific functions—for example, the domestication of autonomous vehicles may differ substantially from that of smartphones. While the distinction is beyond the scope of the present study, it constitutes an important avenue for future research.

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Declarations

Ethical approval and consent to participate

Conducted in line with the Declaration of Helsinki, this study received ethical approval from the Humanities and Social Research Ethics Committee (HSSREC), Institute of Sociological Sciences, John Paul II Catholic University of Lublin (2023-11-02, ref. no. 12/2023).

Availability of data and materials

The datasets used and analyzed during the current study are available from the authors on reasonable request.

Competing interests

The authors declare that they have no competing interests.

Appendix

Questionnaire items used to measure key variables included in the study. Each item was rated on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree).

Z06 Trust in AI: Would you decide to:
- Mark each item on the scale with an ‘x,’ where 1 means strongly disagree and 5 means strongly agree
- Replace your traditional car with an autonomous car using AI technology
- Use medical services where doctors are replaced by AI
- Entrusting AI with performing independent financial transactions on your behalf
- Entrusting AI with legal services
- Entrusting AI with taking over your professional duties
- Entrusting AI with caring for your child

Z02 Describe your behaviour in relation to the following statements:
Mark the appropriate answer on the scale, where 1 means strongly disagree and 5 means strongly agree; 0 = not applicable (e.g. I do not use, I do not have parents, etc.)
- I feel ‘guilty’ when using texts written by AI because they were not written by me
- I am convinced that I use AI responsibly
- Someone in my environment (e.g. parents, partner) monitors my access to AI technology
- I prefer to communicate with AI using voice commands
- I prefer to communicate with AI in writing
- I can tell whether a given text was written by humans or by AI
- I can recognise when I am talking to a chatbot based on AI technology
- I can tell whether a given graphic was created by humans or by AI

P11 Imagine the following situation: AI controls an autonomous car. The car caused an accident. Who do you think is responsible for causing the accident?
Mark each option with an ‘x’ on the scale. Mark the correct answer on the scale, where 1 means strongly disagree and 5 means strongly agree.
- Owner/rental company
- Passengers
- Car engineers
- AI programmers

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