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"There Are Risks, but I Will Use It Anyway": Predicting the Urge to Regulate and the Intended Use of Generative AI Among Youth in Four Countries

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ABSTRACT

Generative AI is rapidly evolving, yet our understanding of how the public assesses and evaluates this technology remains limited. This is particularly true for youths who traditionally are early adopters of new technologies. Our study investigates how sociodemographic variables as well as risk perceptions influence youths' future urge to regulate as well as their future intention to use generative AI in Indonesia, Austria, Serbia, and Hong Kong (China). Using quota-based survey data, we find a limited explanatory value of sociodemographic variables. Interestingly, our findings suggest that information-related risks cannot increase the urge to regulate as well as dampen the intended use among youth. However, perceived social risks unequivocally explain the urge to regulate across countries. Also, the effect of perceived social risks on the urge to regulate is reduced with rising levels of prior use of generative AI. By and large, findings suggest that young individuals perceive risks, but that does not necessarily dampen their own willingness to use generative AI. Implications are discussed. This study is among the first to offer cross-cultural insights into how youth across both European and Asian contexts perceive and engage with generative AI.

1 | Introduction

In recent years, technological advances in artificial intelligence (AI) have marked a significant change in societal practices with technology [1]. In particular, generative AI—with its most prominent recent example ChatGPT—refers to a technology that responds to users' prompts by generating texts delivering fast and comprehensive information about all aspects of human life. Large language models that generate content, such as ChatGPT, are considered to have disruptive potential across many societal facets due to being freely accessible and producing convincing, human-like text. Although one may argue that ChatGPT and other generative AI technology will not replace human involvement across many domains, they may concern almost every aspect of our lives, from fulfilling information-related tasks to shaping how humans interact with each other and how they define and see themselves [2–4]. Advancements in generative AI technology (e.g., Meta's Llama and Google's Bard) will stay in human environments and, therefore, might lead to societal transformations [2, 4–6]. Due to potential harmful

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transformations, perceptions of generative AI–related risks might increase.

When looking at the future potential of generative AI, young people are particularly important. Generative AI concerns questions of learning, knowledge acquisition, and education, which is particularly relevant for younger individuals. More importantly perhaps, when it comes to the responsible use of generative AI, younger generations are typically the early adopters and set the agenda for how this technology is discussed, used, and accepted. Young individuals' awareness of potential risks is therefore extremely important for assessing the future impact of generative AI on society.

In this study, we follow the World Health Organization (WHO)[7] definitions of youth and focus on the middle to late adolescence and young adulthood period (16–24 years old). Research indicates that this age group is actively using generative AI [8], with ChatGPT emerging as the most widely used generative AI among internet users aged 16 and above. During this period, several important developmental tasks arise, such as finding one's personal identity and developing an individual self-concept [9]. Youth are also early adopters, which may shape how generative AI is used in the future. Thus, we argue that late adolescence, as well as young adulthood, is a key period where adolescents adopt and adapt AI, potentially forming long-lasting usage patterns that are relevant for regulating AI and willingness to use generative AI in the future (see [8, 10]). Given the transformative potential of generative AI, especially for youth, understanding how perceived risks shape their attitudes toward regulation and use is essential for anticipating societal responses to this technology [11].

Although we know from prior research that the youth is particularly likely to adopt generative AI, less is known about the risks they perceive and how these risks shape the urge to regulate as well as future intended use in youth. Furthermore, we lack a clear picture of which sociodemographic variables may predict the urge to regulate as well as the intended use for this age group. More important, there is a pressing need for cross-country research. In fact, cross-country research is essential to capture the diverse perceptions and adoption patterns of AI technologies globally. Existing studies mainly focus on Western nations and select industrialized Asian countries, leaving a gap in understanding perspectives from the Global South and less-studied European regions [12–14]. This cross-country study addresses this research gap by examining the urge to regulate as well as the intended use of generative AI among youth in Austria, Hong Kong, Indonesia, and Serbia. To address this gap, we pose the following research question: How do the relationships between sociodemographic factors, risk perceptions, and attitudes toward generative AI (urge to regulate and intended use) differ across Austria, Hong Kong, Indonesia, and Serbia? To our knowledge, this is one of the first comparative studies examining how youth in both European and Asian contexts perceive and respond to generative AI. Including Austria, Hong Kong, Indonesia, and Serbia allows for a culturally and economically diverse perspective that is rarely represented in current AI research. Findings provide incremental insights into how young individuals perceive this skyrocketing technology, with important consequences for how societies will deal with generative AI in the years to come.

2 | Conceptualizing Youth Regulation and Use of Generative AI

Generative AI refers to "computational techniques that are capable of generating seemingly new, meaningful content such as text, images, or audio from training data" ([13], p. 111). Some examples of this revolutionizing technology include ChatGPT-5, Bard, and Copilot among other tools and platforms. These large language models have the potential to dramatically change the way we work and communicate with each other, but also the way we perceive and interact with advanced technologies. Recent research has focused on several key processes of technology adoption and use, mainly in relation to theories such as computers-are-social-actors [14], technology acceptance model [15], and protection motivation theory (PMT) [16]. These theories explain how, why, and under what conditions users accept and adopt new technologies (e.g., [17, 18]). Although these theories have different focal points, scholars agree that models only explaining the initial use of technology are inherently limited. Recent research distinguishes several phases. De Graaf et al. [17] theorize six acceptance phases for interactive technologies: expectation, confrontation, adoption, adaptation, integration, and identification. Therefore, to understand the individual and societal implications of generative AI, we need to examine the factors that shape acceptance. In particular, regulatory frameworks are crucial, and more importantly, how the public thinks about regulation.

2.1 | The Urge to Regulate

In fact, significant concerns about the need for human regulation have been voiced. Central to this is the concept of meaningful human control, which argues that humans must retain ultimate authority and moral responsibility over AI systems to ensure their trustworthiness and ethical alignment [19]. The AI control problem has been identified as one of humanity's most pressing challenges, highlighting the critical need for effective oversight of AI behaviors [20]. Explainable AI plays a vital role in this context by enabling users to understand, justify, and challenge decisions made by automated systems [21]. People's desire to regulate AI varies based on factors like task relevance and personal significance. Individuals are more inclined to use AI tools when granted a certain level of control [22].

Also, young people emphasize the necessity for regulation and surveillance of AI development and usage. They advocate for global cooperation to establish safeguards, expressing concerns that overreliance on AI could lead to destructive dependence [23]. Recent studies show that youth engage with generative AI in different ways than older age groups, often with greater openness but also less structured guidance or regulation [9, 24]. This generational gap in exposure and expectations may lead young people to hold both a higher perceived need for regulation and a greater willingness to explore AI use [25, 26]. These differences can also be understood through youth-specific trajectories of technology acceptance, as younger users may more quickly move through phases like adoption, adaptation, and integration [17]. Furthermore,

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some scholars argue that AI development is predominantly Western-centric, potentially overlooking diverse cultural perspectives [27]. Recognizing this, there is a call for inclusive approaches in AI governance to address global diversity. The instinctive human need to maintain control over technology underscores the powerful motivation to ensure responsible AI development and use [28].

2.2 | Intended Use

Besides regulation, intended future use is an important variable in understanding youths' acceptance of generative AI. In our study, we aim to cover several processes involving young individuals' use of generative AI, the roles of indirect experiences through mass or social media, and perceptions of generative AI. Since the emergence of generative AI, young individuals started to increasingly use and adopt various AI tools and platforms [6] even more so than older generations [29]. Despite high initial usage rates, it remains unclear whether young adults plan to continue with the use of generative AI in the future and how willing they are to rely on it for obtaining information. In fact, 34% of young individuals who have never used generative AI reported it would not be helpful for them, and only 4% reported being daily users [24]. Many have also reported risks related to work loss, privacy concerns, information biases, and so on. Due to increasing perceptions of risks related to generative AI, the willingness to use generative AI might decrease. Previous studies on AI have shown high perception of risk was related to less risk-taking behavior (e.g., [30, 31]), and the high-risk perception of AI was associated with a lower probability to use AI, whereas a high opportunity perception of AI was related to a higher probability of using AI [32].

3 | Key Predictors of Youth Generative AI Attitudes: Demographics, Risks, and Usage

3.1 | Sociodemographic Predictors

Given these diverse attitudes and the influence of demographic factors, it is crucial to investigate how sociodemographic characteristics predict individuals' willingness to use generative AI and their urge to regulate it. We focused on age, gender, and education because these variables are consistently identified in the literature as key predictors of digital technology adoption and risk perception (e.g., [35, 36]). Since our aim was to test a clear and focused model, we selected only the most commonly used and theoretically relevant variables for youth. Such evaluation can clarify the interplay between demographic variables and AI perceptions, forming the basis for our forthcoming hypotheses. Although generative AI offers numerous capabilities and becomes increasingly integrated into everyday digital interactions, its adoption and acceptance vary significantly across different age groups. Although the studied age range (16–24) may appear narrow, previous research suggests that meaningful differences in digital literacy, independence, and online behaviors can emerge even within this developmental period (e.g., [37, 38]). Older youth are typically more experienced and autonomous in navigating technology, which may influence their perceptions of risk and attitudes toward AI regulation. A substantial majority of online teenagers aged 13–17 are engaging with generative AI tools and services, with 79% reported usage [8]. Older adults display particularly pronounced concerns regarding online safety and privacy, actively adopting measures to mitigate these risks [39]. According to a recent survey conducted among early and late adolescents, [37] showed that older adolescents had not only greater awareness of the privacy implications of online activities but also engaged more deeply in proactive privacy management. Older adolescents recognize that their online actions impact their reputations and future academic or career paths [38]. All of this leads us to suggest that age relates to a stronger urge to regulate and lower usage intentions. Thus, we formulate this hypothesis:

H1: Older age predicts (a) a higher urge to regulate AI and (b) a lower intention to use generative AI.

Research has consistently shown that women are generally more cautious about their online safety, expressing concerns over cybersecurity and the protection of personal information compared with men [35, 40]. This caution is reflected in the usage statistics for generative AI services such as ChatGPT, which, despite its popularity among internet users aged 16 and above (23% usage), sees a gender disparity among younger users with boys significantly more engaged (34% vs. 14%) [8]. This gender-based variation extends to perceptions of privacy and vulnerability to online risks. Girls are particularly sensitive to privacy issues associated with mobile apps and devices, driven by concerns over location tracking [38]. Further illustrating this divide, boys exhibit more risky online behaviors and lower awareness of the consequences associated with the sharing of personal data and photographs [41, 42]. H2 is as follows:

H2: Women will express more (a) urge to regulate generative AI and (b) less intention to use generative AI in the future than men.

Research has highlighted how socioeconomic factors influence online behavior and privacy concerns, particularly among younger users. For instance, children from lower socioeconomic backgrounds are less likely to have public social media profiles or share personal data, pointing toward a cautious approach to online engagement [43]. Moreover, the educational level of parents plays a crucial role in shaping children's online privacy concerns. Teens whose parents possess higher educational qualifications tend to exhibit heightened awareness and concern regarding their online privacy, likely due to more effective parental mediation strategies [44]. These insights are complemented by findings that interactive learning materials significantly enhance privacy-related knowledge among children as young as seven, with improvements in privacy knowledge and behavior still evident 1 week after intervention [43]. Additionally, adults with higher education levels not only engage in more proactive online safety practices but also possess more knowledge of online security measures [35]. This correlation suggests that educational level is closely linked to both the understanding and implementation of online safety behaviors. Furthermore, a recent study showed that students' positive attitudes toward generative AI technologies and their integration into learning and future careers correlate with their knowledge and frequent usage, enhancing their likelihood to continue using these technologies

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[36]. Similarly, despite significant concerns about its societal implications, the most prolific users of generative AI—online 16–24-year-olds—continue to engage heavily with the technology, suggesting that their perceived benefits from using AI may outweigh their awareness of potential risks [8]. Given these insights, we hypothesize the next hypothesis:

H3: Higher education predicts (a) more urge to regulate AI and (b) more intention to use generative AI.

3.2 | Risk Dimensions

Several risks may arise with respect to generative AI. Studies have pointed to various aspects of risks associated with online interactions; however, no study to date has comprehensively tested different dimensions in a single framework. We propose that generative AI can include *information*, *relationship*, and *identity risks*. These three dimensions are intertwined, necessitating a comprehensive analytical understanding. First, due to the acquisition of information in terms of searching and receiving health information, the information risks concern all processes related to information exposure, selection of valid and truthful information, as well as questions of learning about specific issues. Information risks also include privacy-related aspects, data security, or information theft. One of the core concerns of researchers and the public is that generative AI might produce and facilitate incorrect information. For instance, the most discussed risk is that information generated via ChatGPT might lead to spreading misinformation or distorting scientific facts [45]. Studies evaluating generative AI outputs show overall low accuracy [46]. For youth, information risks are particularly relevant: Young people increasingly rely on generative AI for information acquisition [8]; they may be less likely to use traditional information sources to check the information provided by generative AI. Also, young people are still developing their critical thinking skills, making them particularly vulnerable to misinformation [47].

Second, relationship risks refer to processes with respect to human–human (i.e., interpersonal) and human–technology relations, and how these are affected by generative AI. Research evidence suggests that people often intuitively perceive any kind of social cues in relation to technology not as an object but as some kind of being, according to the computer-are-social-actors paradigm [16]. People can attribute human-like qualities to machines based on communicative abilities and behavior and in many cases treat them as trusted companions (e.g., [48]). For youth, relationship risks are relevant because youth critically need peer interaction to develop social skills. An overreliance on generative AI, as for instance with AI companionship, may lead to unrealistic expectations and distort these processes.

Third, identity risks include a sense of identity in light of generative AI, as well as the formation and change of identity as users of generative AI. According to the self-extension theory [49], technology has the potential to augment individuals in a functional way in order to achieve desired goals. This functional extension of identity has been found in the context of the habitual use of smartphone devices for various purposes [50, 51]. However, problematic use of technology has been found to increase identity changes [51]. Identity shifts might occur as negative processes in regard to ChatGPT use in areas of self-presentation [52], loss of control over impression management [53], as well as identity attribution and sense of intelligence [54]. For youth, identity risks are relevant because youth is generally a critical period for identity development. Generative AI may influence norms of idealized self-representation and authenticity.

How do these risks shape the urge to regulate and intentions to use? According to PMT [18], risks evoke specific coping behaviors such as increased control and reduced usage. PMT suggests that when individuals perceive a high risk, they are motivated to engage in protective behaviors to avert potential threats [18]. PMT is particularly relevant in the context of generative AI, where the novelty and complexity of the technology can intensify perceptions of risk. As individuals become more aware of the short- and long-term risks associated with new AI technologies such as security risks (cyber intrusions and privacy risks), control risks (inability to control malevolent AI), ethical risks (lack of values), economic risks (job displacement and reputation risks), societal risks (risk of "intelligence divide"), and AI-generated misinformation risks [55], their responses may include increased protective measures [56]. For instance, it is observed that as adolescents mature, they become more protective of their privacy and cautious about their online circles, reflecting a growing awareness and response to perceived online risks [57]. Moreover, a recent study by Tu and Li [58] has indicated that risk perceptions can mediate the relationship between technology use and self-protective behaviors, affecting both personal and societal levels. This negative influence on usage intentions can be attributed to people's perception of risks, which makes the technology seem less beneficial if they distrust it or see it as dangerous [59].

Extant research in various online contexts has shown that higher perceived risks lead to reduced usage. For instance, individuals who are attracted to the usefulness of an app are likely to have higher concerns for privacy and therefore engage less [60]. In e-commerce, perceived risks not only lower perceived usefulness but also negatively impact online engagement behaviors [61]. Similarly, users of chatbot services report lower satisfaction and reduced usage intentions when they perceive high privacy risks [62]. Therefore, we can assume the same process in the context of rapidly evolving generative AI use and associated risks. Given the previous research insights and theoretical background, our hypothesis is formulated as follows:

H4: Risk perceptions related to generative AI positively predict the (a) urge to regulate generative AI and negatively predict (b) intention to use generative AI.

3.3 | Generative AI Use as a Moderator

The dynamics of how individuals perceive and interact with generative AI are significantly influenced by their cognitive biases and levels of familiarity with the technology. A phenomenon similar to the third-person effect in media influence reveals that practitioners anticipate major changes induced by AI in their profession but perceive these changes as less impactful in their own organizations and even less so on a

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personal level [63]. This cognitive bias affects how the risks and benefits of AI are perceived across different professional contexts. Young users, in particular, may experience the third-person effect differently than older adults [63]. Due to their increased exposure to social media and online peer comparison, they might underestimate how generative AI affects themselves while overestimating its influence on others, especially within their social networks [26]. This can lead to reduced personal concern, despite general awareness of risks. Additionally, prior use and experience with generative AI may foster a sense of familiarity or even overconfidence among youth. Frequent users might feel more capable of managing potential harms, thereby weakening the impact of perceived risks on their desire for external regulation [36]. These dynamics make young people's use of generative AI a particularly important moderator to consider when studying attitudes toward AI governance.

Further research highlights the complex interplay between people's perceptions of risks and opportunities (ROP) associated with AI and their willingness to engage with the technology. Another study has shown that a higher ROP score, indicating a balance skewed more toward seeing opportunities than risks, correlates with a higher likelihood of AI adoption. If two individuals have similar risk perceptions, the one with a more optimistic view of AI's potential benefits is more likely to use it [34]. This suggests that opportunity perception significantly moderates the relationship between risk perception and AI engagement. Additionally, a study on students' engagement with generative AI technologies found that both the knowledge about and frequency of using generative AI are positively correlated with the willingness to use these technologies in the future [36]. This implies that familiarity and habitual use can diminish perceived risks or at least enhance confidence in managing them. Given this background, our hypothesis proposes a specific interaction effect in the context of generative AI use:

H5: For those who use generative AI more, the relationship between risk perceptions and the urge to regulate generative AI is weaker.

4 | A Case for Cross-Cultural Research

Most current research concentrates on Western nations or certain industrialized countries in Asia [12–14], with a lack of comparative studies in Europe and inclusion of the Global South. However, countries differ with respect to their AI regulations and discussions. We focus on two European countries, Austria, which is part of the European Union, and Serbia, which is aimed at integrating into the European Union. Both countries are developing regulations in line with the European Union standards conforming to the EU AI Act. According to AI Landscape Austria research overview [64], there are first implications of the European AI Act shown through a growing number of specialized companies on trustworthy AI, compliance, and regulation that are rapidly emerging. Serbia has adopted ethics guidelines for AI development, implementation, and use to align with the European legislative framework and the 2021 UNESCO AI Ethics Recommendation.

Additionally, we are focusing on two Asian countries, Hong Kong, a technologically advanced and developed economic region, and Indonesia, a Global South country with a rapidly growing digital economy. Although the Hong Kong population demonstrates high interest and traffic when it comes to generative AI tools with 862 searches per 100 k individuals, Indonesia reflects lower search interest among its population with 120 searchers per 100 k individuals [65]. Both countries are rapidly adopting ethical AI regulations, mainly focusing on the prevention of misuse and privacy risks.

When it comes to perceptions about AI, the Ipsos survey indicated significant differences in perceptions about the benefits and limitations of AI. In Indonesia, 78% of respondents feel positively about AI as a technology. However, in several developed Western nations, attitudes are less positive. Trusting AI with issues of discrimination, bias, and data protection is roughly globally at around 50% [66]. This global survey did not include Austria, Hong Kong, or Serbia highlighting a gap in understanding perceptions and attitudes toward generative AI in these regions. Serbia's digital landscape shows a high daily internet usage among students (86%) and significant engagement with social media (74%) [67] yet the country shows low digitalization levels [68]. Austria's AI ecosystem is rapidly advancing with numerous startups and educational initiatives. However, there remains a gap between AI usage and formal AI education, emphasizing the urgent need for integrating AI into the curriculum (AI [64, 69]). In Indonesia, trust and perceived benefits are crucial for adopting digital technologies [70] whereas in Hong Kong, chatbot satisfaction is necessary for user adoption [71] within especially various online communication forms [72].

Youth attitudes toward generative AI are likely shaped not only by individual-level factors such as perceived risk and demographic characteristics, but also by broader cultural and institutional contexts. For example, uncertainty avoidance, a cultural dimension describing how societies cope with ambiguity, can influence regulatory preferences. In high-uncertainty avoidance cultures such as Indonesia and Serbia, individuals may be more inclined to support external controls to manage emerging technologies and reduce perceived societal disruption, whereas in lower-uncertainty contexts like Austria or Hong Kong, youth may emphasize autonomy and individual agency in regulating AI [73][74]). In addition, institutional trust can shape how youth evaluate the necessity and legitimacy of AI regulation. For instance, Austrian youth may perceive government-led initiatives as competent and transparent, reducing perceived personal urgency for regulation [75, 76]. In contrast, in contexts where institutional trust is weaker or more ambivalent, such as in Serbia or Indonesia, young people might either strongly support regulation as a safeguard or dismiss it due to skepticism about its effectiveness [77]. Technological optimism and digital culture also vary across countries. In Hong Kong, rapid digitalization and familiarity with new tools may foster a more pragmatic view of AI, with youth perceiving both ROP but favoring innovation [78]. Meanwhile, in Serbia, where digital infrastructure is still developing and digital education varies widely, young people may perceive generative AI as both promising and threatening, depending on their individual exposure and digital competence [79]. These structural and cultural differences suggest that the strength and direction of relationships

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between predictors (e.g., risk perception and sociodemographics) and outcomes (regulation and use) may differ significantly across countries. Given these insights, we are aimed at exploring if our assumptions about young people's urge to regulate and intentions to use generalize across these diverse contexts, leading to our research question:

RQ: How do the relationships stated in H1–H5 differ between Austria, Hong Kong, Indonesia, and Serbia?

5 | Method

5.1 | Sample

We conducted a cross-sectional online survey in four countries, Austria, Hong Kong, Indonesia, and Serbia. We applied country-specific quotas for gender and age, and soft quotas for education. The idea was that the samples should be in line with basic characteristics of respondents in the studied countries. We had to use soft quotas for education because the polling company was unable to secure full quota for education in all countries. More complex quotas were not feasible. The IRB at the Department of Communication at the University of Vienna approved the study (Confirmation Number: 993). Data were collected between March 12, 2024 and April 10, 2024 by private polling companies. We sampled individuals aged 16–24 years who use at least one major social media platform (Facebook, YouTube, X/Twitter, Instagram, TikTok, WeChat, Sina Weibo, or WhatsApp). For data quality purposes, we excluded 200 individuals who either failed two attention checks ($n = 65$) or were identified as speeders ($n = 135$). Speeders were defined as respondents that took less than one-third of the country's median time since it is unlikely that most of the survey's instructions and items were read by these individuals. The final sample consists of $N = 2144$ respondents (Austria: $n = 505$; Hong Kong: $n = 600$; Indonesia: $n = 536$; Serbia: $n = 503$). We aimed for a sample size of $n = 500$ per country based on considerations of statistical power necessary to test the hypothesized relations. Also, since Serbia and Austria are small countries, the sample size appeared as feasible. More specifically, with approximately 500 respondents per country, our study has $\geq 80\%$ power ($\alpha = 0.05$, two-tailed) to detect small effects—per country, which was deemed as sufficient.

Table 1 features the demographic composition per country. The samples for Hong Kong and Indonesia were older than the target population. Further, in Hong Kong, males were slightly overrepresented. Educational background was diverse. Data are available on the OSF (https://osf.io/fmj3v/?view_only=2692e1a89b1e4271b226d5cad448198a).

TABLE 1 | Demographic composition for each country.

	Austria	Hong Kong	Indonesia	Serbia
Gender: male	50.10% ($n = 253$)	48.33% ($n = 290$)	51.31% ($n = 275$)	50.89% ($n = 256$)
Gender: female	49.50% ($n = 250$)	51.50% ($n = 309$)	48.51% ($n = 260$)	49.11% ($n = 247$)
Gender: diverse/other	0.40 ($n = 2$)	0.17% ($n = 1$)	0.19% ($n = 1$)	0.00% ($n = 0$)
Age: 16–19 years	42.18% ($n = 213$)	29.67% ($n = 178$)	37.31% ($n = 200$)	42.74% ($n = 215$)
Age: 20–24 years	57.82% ($n = 292$)	70.33% ($n = 422$)	62.69% ($n = 336$)	57.26% ($n = 288$)

5.1.1 | Measures

The questionnaire was designed in English. We used a translation back-translation process. Native speakers who were familiar with the research topic translated the questionnaire to the respective language before the translations were back-translated to English by another native speaker. Afterward, the two native speakers and one of the authors met to discuss the differences and resolve any disagreements. We were looking for potential differences in meaning, tone, or intent. No major issues emerged.

5.1.2 | Risk Perceptions Related to Generative AI

We assessed risk perceptions regarding information, relationships, and identity dimensions with 12 self-developed items. On a 7-point Likert scale ranging from 1 "strongly disagree" to 7 "strongly agree", respondents stated their agreement with the following statements for information risks: (1) Generative AI is likely to spread misinformation; (2) generative AI is likely to produce biased information; (3) generative AI is likely to produce information that manipulates people; and (4) generative AI is likely to output information that omits important pieces. For identity risks, we included statements such as: (1) When humans use generative AI, they will feel less capable of solving problems on their own; (2) the use of generative AI will negatively affect how humans evaluate their own skills; (3) using AI might make people doubt what they are capable of; and (4) because of generative AI, people will doubt their skill set and themselves. For relationship risks, the statements were as follows: (1) Generative AI will harm social relationships; (2) because of generative AI, humans will rely less on each other; (3) generative AI has negative consequences for how we treat each other; and (4) generative AI will be bad for our social connections with others. When including all items in the exploratory factor analysis, the results showed two dimensions of *information risks* (Cronbach′s alpha = 0.88; $M = 4.01$, SD = 1.5) and *social risks* consisting of identity and relationship items (Cronbach′s alpha = 0.93; $M = 4.13$, SD = 1.49). Next, we conducted confirmatory factor analysis (CFA) including 10 items in two dimensions, four items reflecting information risks and six items reflecting social risks. The CFA model showed good fit: CFI = 0.97; TLI = 0.96, $\chi^2/\mathrm{df} = 8.78$; $p < 0.001$; RMSEA = 0.08, SRMR = 0.04, 90% CIs [0.07; 0.08]. All items had significant standardized loadings, > 0.70 in both dimensions. Based on the factor-analytic findings, we were unable

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to proceed with the three dimensions and can only work with two dimensions.

5.1.3 | Urge to Regulate

We measured the urge to regulate AI based on [80]) and Liu [81]. Respondents were asked to state their agreement on a 7-point Likert scale ranging from 1 "strongly disagree" to 7 "strongly agree" with the following statements: "The government should issue policies to guide generative AI development," "An international treaty should manage generative AI development," "An agreement should regulate the scientific domain for generative AI research and development," and "Policies should guide generative AI's commercial development" (Cronbach′s alpha = 0.91; $M = 4.62, \mathrm{SD} = 1.59$). The items capture distinct but related facets of regulation (governmental, international, scientific, and commercial domains), thereby representing the content domain of AI regulation attitudes. Empirically, a CFA further supported construct validity, with all items loading strongly ($\lambda > 0.70$) on a single factor, and nested model comparison demonstrated that urge to regulate is different from willingness and frequency of generative AI use as well as risk perceptions. This clearly demonstrates construct validity.

5.1.4 | Willingness to Use Generative AI

Two items were included to measure future intention to use generative AI: "I think I will use generative AI in the future" and "I am willing to use generative AI in the future" ($r = 0.78$, $p < 0.001$; Cronbach′s alpha = 0.88). The items captured individuals' behavioral intentions toward future AI use, a construct theoretically grounded in the technology acceptance model [17]. Empirically, the two items were highly correlated, reflecting a single underlying construct, and they are distinct from urge to regulate and risk perceptions in terms of a nested model comparison.

5.1.5 | Frequency of Generative AI Use

On a 7-point scale ranging from *never* to *very often*, we asked participants: "Over the last month, how often have you used generative AI such as ChatGPT, GPT-F, or Bard?" ($M = 4.34$, SD = 2.12).

5.1.6 | Control Variables

We included age, gender, education, and media use as covariates. For media use, on a 7-point scale ranging from *never* to *always*, we asked participants how often they consume (1) TV news; (2) newspapers; (3) radio; (4) online websites; and (5) social media (Cronbach′s alpha = 0.76; $M = 3.96$, SD = 1.46).

5.2 | Data Analysis

We conducted a path analysis with observed variables in R with the lavaan package using a maximum likelihood estimator. We predicted two dependent variables: (1) urge to regulate generative AI and (2) intention to use generative AI in the future. The independent variables were information risks and social risks; the moderating variable was the frequency of generative AI use, and the control variables included age, gender, education, and media use.

The correlations between the variables are displayed in Table 2.

6 | Results

Findings are shown in Table 3. With respect to our first hypothesis, we found no relationships between age and urge to regulate as well as intention to use. Only in Indonesia, there was a positive relation for both the urge to regulate ($b = 0.05$, $p = 0.02$) and the intention to use ($b = 0.07$, $p = 0.01$). Thus,

TABLE 2 | Zero-order correlations between the key variables.

	1	2	3	4	5	6	7	8	9
1. Age	1								
2. High education	0.40**	1							
3. Middle education	−0.18**	−0.77**	1						
4. Gender	0.09**	0.09**	−0.05**	1					
5. Frequency of GAI use	−0.02	0.15**	−0.09**	−0.10**	1				
6 Informational risk perceptions	0.02	0.12**	−0.08**	0.03	0.14*	1			
7. Social risk perceptions	−0.01	0.06**	−0.04**	0.10**	0.05*	0.66**	1		
8. Willingness to use GAI	0.02	0.08**	−0.02	−0.12**	0.41**	0.21**	0.15**	1	
9. Behavioral intention regarding GAI regulation	0.08**	0.11**	−0.04	0.05*	0.20**	0.40**	0.46**	0.52**	1

Note: $N = 2144$.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

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TABLE 3 | Results of the hypothesized relationships.

	Dependent variables							
	Urge to regulate generative AI				Intention to use generative AI			
	Austria	Serbia	Hong Kong	Indonesia	Austria	Serbia	Hong Kong	Indonesia
	b (SE)	b (SE)	b (SE)	b (SE)	b (SE)	b (SE)	b (SE)	b (SE)
Age	−0.01 (0.02)	0.04 (0.04)	0.01 (0.02)	0.05* (0.03)	−0.00 (0.03)	−0.01 (0.04)	0.02 (0.02)	0.07* (0.03)
Female	−0.11 (0.11)	0.02 (0.15)	0.24** (0.09)	−0.04 (0.11)	−0.58*** (0.13)	−0.46** (0.15)	0.05 (0.10)	−0.38** (0.12)
Middle education	0.09 (0.13)	0.16 (0.28)	1.06 (1.11)	0.18 (0.19)	−0.01 (0.16)	0.13 (0.23)	1.85 (1.26)	0.31 (0.22)
High education	0.07 (0.23)	0.28 (0.28)	0.85 (1.11)	0.33 (0.24)	−0.30 (0.28)	0.16 (0.29)	1.63 (1.27)	0.17 (0.26)
Media use	0.09* (0.05)	0.18*** (0.05)	0.28*** (0.04)	0.32*** (0.04)	0.21*** (0.06)	0.25*** (0.05)	0.19*** (0.05)	0.31*** (0.05)
Generative AI use	0.09 (0.09)	0.09 (0.08)	0.30*** (0.06)	0.33*** (0.07)	0.19*** (0.03)	0.34*** (0.03)	0.22*** (0.03)	0.21*** (0.03)
Information risks	0.06 (0.09)	−0.17(0.12)	0.18 (0.10)	0.22* (0.09)	0.13* (0.06)	−0.06 (0.06)	0.13* (0.06)	0.09 (0.05)
Social risks	0.65*** (0.09)	0.55*** (0.11)	0.33** (0.10)	0.54*** (0.09)	−0.04 (0.06)	0.09 (0.05)	0.11* (0.05)	0.11* (0.05)
Information risks: X generative AI use	0.03 (0.02)	0.06* (0.02)	−0.02 (0.02)	−0.03 (0.02)	—	—	—	—
Social risks: X generative AI use	−0.06** (0.02)	−0.05* (0.02)	−0.02 (0.02)	−0.04* (0.02)	—	—	—	—
R^2	0.31	0.23	0.36	0.39	0.19	0.25	0.28	0.29

Note: *** p < .001, ** p < .01, p < .05.

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by and large, H1a and H1b found no support. When it comes to our second hypothesis, findings were mixed. Female gender was not significantly related to the urge to regulate in Austria ($b = -0.11$, $p = 0.31$), Serbia ($b = 0.02$, $p = 0.88$), and Indonesia ($b = -0.04$, $p = 0.73$), but positively related in Hong Kong ($b = 0.24$, $p = 0.01$). H2a can be falsified. For H2b, female gender negatively predicted intention to use for Austria ($b = -0.58$, $p = 0.00$), Serbia ($b = -0.46$, $p = 0.00$), and Indonesia ($b = -0.38$, $p = 0.00$), but not Hong Kong ($b = 0.05$, $p = 0.61$). This lends partial support for H2b. In contrast to H3a and H3b, education was unrelated to both, the urge to regulate and the intention to use (see Table 3).

As for risk perceptions, findings suggest a limited role of informational risks in predicting the urge to regulate. The relation is only significant for Indonesia ($b = 0.22$, $p = 0.01$), but not for the other countries (Austria: $b = 0.06$, $p = 0.51$; Serbia: $b = -0.17$, $p = 0.17$; Hong Kong: $b = 0.18$, $p = 0.09$). This stands in contrast with H4a. With respect to intention to use, findings are mixed, with significant relations in Austria ($b = 0.13$, $p = 0.03$) and Hong Kong ($b = 0.13$, $p = 0.02$), but not Serbia ($b = -0.06$, $p = 0.29$) and Indonesia ($b = 0.09$, $p = 0.08$).

Social risks, however, emerged as a significant positive predictor of the urge to regulate for Austria ($b = 0.65$, $p = 0.00$), Serbia ($b = 0.55$, $p = 0.00$), Hong Kong ($b = 0.33$, $p = 0.00$), and Indonesia ($b = 0.54$, $p = 0.00$), in line with our expectations. However, they do not negatively predict intentions to use (Austria: $b = -0.04$, $p = 0.09$; Serbia: $b = 0.09$, $p = 0.46$), and even positively predict usage intentions in Hong Kong ($b = 0.11$, $p = 0.03$) and Indonesia ($b = 0.11$, $p = 0.04$). By and large, we find limited support for H4a (i.e., with respect to social, but not information risks), but no support for H4b.

Finally, we were interested in the interaction of risk perceptions and prior generative AI use when predicting the urge to regulate. With respect to information risks, H5 found no support. However, the Serbian data suggest that the effect of information risks on the urge to regulate becomes weaker with rising levels of use (see Figure 1). Thus, the use of generative AI seems to dampen the effect of risks on the urge to regulate. For, Austria, Hong Kong, and Indonesia, however, no such pattern emerged. Interestingly, a similar pattern can be found with respect to social risks in three out of four countries. That is, the effect of social risks becomes weaker with rising levels of generative AI use in Austria ($b = -0.06$, $p = 0.00$), Serbia ($b = 0.05$, $p = 0.02$), and Indonesia ($b = -0.04$, $p = 0.04$). This suggests that generative AI use dampens the influence of risk perceptions on the urge to regulate. These interactions are visualized in Figures 2, 3, and 4.

Our research question asked about country differences. Across countries, by and large, we see that the explanatory value of sociodemographic variables is limited. However, findings underline the relevance of social risks across all four countries. The influence of information risks on the urge to regulate and intention to use is, however, highly dependent on the country's context and generally limited. When it comes to the interaction of risk perception and prior use of generative AI, only Hong Kong stands out.

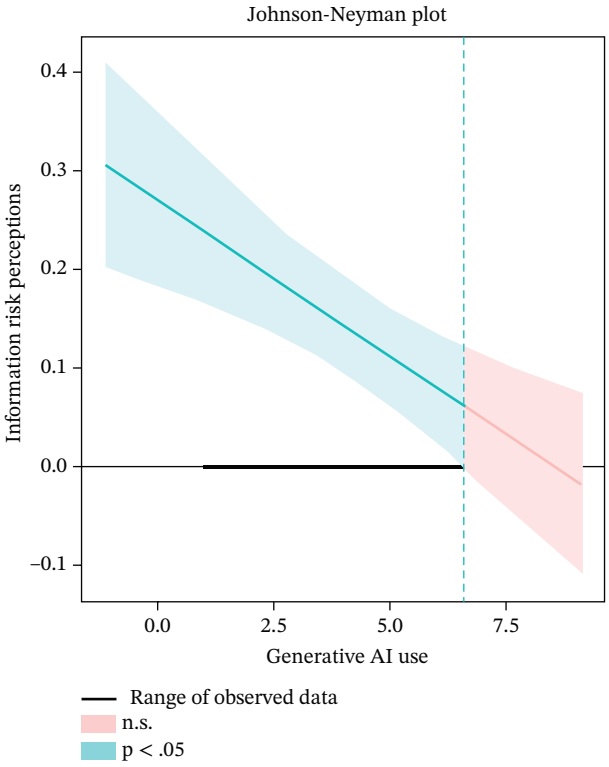


FIGURE 1 | The interaction between information risk perceptions and urge to regulate generative AI moderated by generative AI use presented in the Johnson–Neyman plot (Serbia).

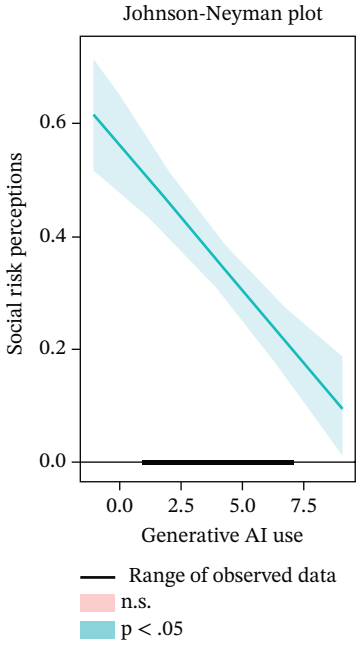


FIGURE 2 | The interaction between social risk perceptions and urge to regulate generative AI moderated by generative AI use presented in the Johnson–Neyman plot (Serbia).

7 | Discussion

Using survey methods from four countries, spanning Europe and Asia, we found limited explanatory value of sociodemographic variables across countries, with the exception of females

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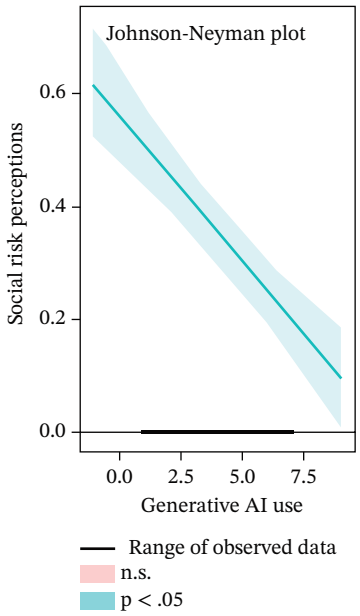


FIGURE 3 | The interaction between social risk perceptions and urge to regulate generative AI moderated by generative AI use presented in the Johnson–Neyman plot (Austria).

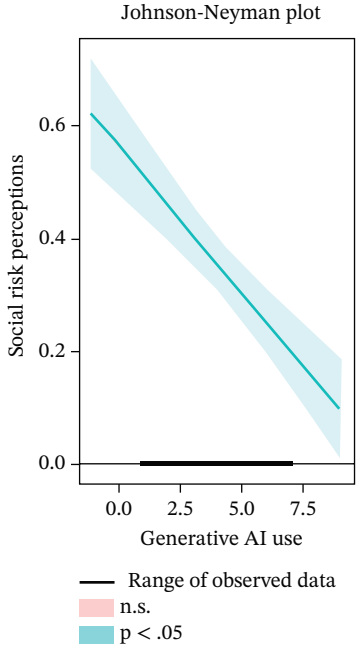


FIGURE 4 | The interaction between social risk perceptions and urge to regulate and regulate generative AI moderated by generative AI use presented in the Johnson–Neyman plot (Indonesia).

being less likely to use generative AI in three out of four countries. This is somewhat surprising and in contrast to some earlier research on AI. One could argue that age plays a limited role in this study because the age span of the sample was rather narrow. Also, education may be of limited predictive value, since generative AI spans all aspects of social, cultural, and political life. Generative AI does not provide expert information; by contrast, it can satisfy all informational needs that one may have, be it physics or more shallow entertainment. It is not a "nerd technology" anymore. Importantly, there is a low entry barrier to the use of generative AI because it is for free and the design is largely intuitive. Age, gender, and education, therefore, do not significantly predict who intends to use the technology. Also, generative AI provides relevant information for everyone, no matter the specific interests or background; it is relevant for all ages, genders, and educational levels.

More importantly, our findings suggest that informational risks do not lead to a larger urge to regulate or a reluctance to use generative AI in the future. In Austria and Hong Kong, the perception of information risks was even positively associated with the intended use of generative AI. This is somewhat surprising. With respect to the urge to regulate, we can offer three explanations: First, one could argue that youth is desensitized when it comes to informational risks. That is, youth has grown up with modern technology and they got used to technology-related risks such as privacy concerns or misuse of data. Informational risks may be perceived as normal. Second, and in line with that, young individuals feel particularly competent when it comes to technology, so they may have the perceived competence to deal with issues related to misinformation and bias. In other words, they have the impression that they are able to recognize and filter out informational risks, and thus, regard regulation as unnecessary, even when they see the risks. Third, the youth may be skeptical about the success of regulation and they may regard policy regulation as a restriction or limitations with respect to their own actions. Regardless of the explanation, we clearly see that information risks do not lead to a higher urge to regulate and a lower intention to use.

The situation is different when it comes to social risks. Across all countries, social risks predict the urge to regulate. That is, the notion that generative AI may make us less capable of solving problems, increase doubt about our skill set and ourselves, as well as harm our social relationships and social connections seems to foster the call for stronger regulation. Here, young people may clearly see the dangers of generative AI with respect to their own lives. Perhaps social risks are more obtrusive to adolescents and more closely related to their daily needs and concerns. Therefore, they are a key driver of regulation attitudes.

When it comes to intended use, the role played by social risks varies across countries. For Hong Kong and Indonesia, social risks were positively related to intention to use. Again, this is surprising and against our expectations. When offering an explanation, one could point to the significant role that technology adoption plays in Asian countries as compared with European countries. Indonesia and Hong Kong can be considered as aspirational technology cultures, and thus, risks associated with a technology may not be a suppressor, but a driver to technology adoption. However, more in-depth evidence is needed to corroborate this claim.

By and large, we see that risk perceptions with respect to generative AI do not prevent young people from intending to use the technology. We can offer three explanations: First, young adults may perceive the risks but believe they are competent enough to handle them. That is, the youth may feel empowered by AI technology, leading to the belief that they can control it. Second, one could argue that the risks are perceived as psychologically distant. That is, although risks are acknowledged, they do not

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appear particularly close or urgent. This leads to a downplaying of risks. Third, perhaps the risks are acknowledged, but not fully understood. The youth may perceive the risks as abstract, without a more in-depth understanding of what these could mean for their lives. Regardless of these explanations, it should be noted that the relations between risk perceptions and intentions to use were tested while controlling for different demographic factors. However, although we tested the moderating role of prior AI use, digital literacy levels or exposure to AI-related harms may moderate this relationship. That is, for individuals with higher literacy or individuals with a history of experienced harms, perceived risks may negatively predict use. Future research should further test these explanations.

When it comes to the interaction of informational risks and prior AI use on the urge to regulate, we found a positive effect for Serbia only. This effect signals that informational risks lead to a higher urge to regulate with rising levels of prior use. Perhaps Serbian citizens may have a higher sensitivity to a potential misuse of technology by political authorities, because—as typical for postcommunist countries—there is a lower trust in institutions as compared with Indonesia, Austria, or Hong Kong.

Finally, when predicting the urge to regulate, an interesting pattern was observed when combining social risks and prior generative AI use. In all countries but Hong Kong, we observed that the effect of social risks on the urge to regulate was dampened by adolescents' own use of generative AI. That is, own prior use reduces the impact of risk perception. One possible explanation for this finding is that familiarity with technology may reduce the weight of the anxieties and concerns associated with it. In other words, using generative AI may lead to a feeling of comfort and competence, potentially fostering the impression that risks are manageable and can be handled well. Thus, regulation appears less urgent. Rephrased, it can be assumed that the use of generative AI leads to a feeling of self-competence, efficacy, and general literacy. These impressions are inherently subjective and may or may not correspond with objective levels of competence or literacy. As another explanation, one may speculate that the youth gets used to the risks, that is, young individuals may become desensitized to certain risks, and thus, they see less need for regulation. More research, particularly qualitative research, is needed to shed light on these explanations.

The absence of the moderating effect of social risks and prior use for Hong Kong is particularly noteworthy. Social risks may be perceived as more politicized in Hong Kong as compared with the other countries. Thus, even adolescents who use generative AI may remain highly attuned to its potential for harm when they perceive social risks, and thus, prior use does not reduce the impact of social risks.

Besides these main findings, we also observed a negative effect of female gender on usage intention across three countries. This may be explained by other research demonstrating that women report lower self-efficacy in using advanced digital tools as compared with men (e.g., [82]). However, the effect was not observed for Hong Kong, perhaps because Hong Kong has a less gendered tech culture as compared with the other countries. Finally, the explained variance for both dependent variables ranges between 19% and 39%, which can be considered a moderate and practically meaningful portion across countries.

7.1 | Current Use Versus Future Use

The dependent variables in this study capture future-oriented constructs, reflecting anticipated behaviors and regulatory attitudes rather than current usage patterns. As the adoption of generative AI is likely to increase over time, the primary value of the present work lies not only in explaining current behaviors but also in anticipating future trends. Based on the findings, it can be assumed that young people will continue to use generative AI despite being aware of its risks. At the same time, public discourse around regulation may intensify as both informational and social concerns gain prominence. Educational initiatives are also likely to expand, aiming to raise awareness and promote responsible use among youth. In this evolving landscape, the current findings should be revisited through replication and/or follow-up research to assess how these dynamics unfold over time.

7.2 | Limitations

Several limitations must be noted. Obviously, we cannot draw causal conclusions. What is more, as in all survey research, our insights are based on self-reported data which are subject to biases. There may be measurement challenges when doing cross-cultural research with youth. Youth may use slang, which cannot be translated to another language. In response, we used language in neutral tone to avoid this issue. Also, for youth, social context may determine how the questions are understood. Although we cannot rule out such effects, the questionnaires were carefully checked by native speakers to detect context- and country-specific meanings of items and words. Follow-up studies should try to observe the actual use of generative AI. Related, several results for Hong Kong differed from other countries. Whether this reflects measurement issues, cultural factors, or sample characteristics, cannot be clarified without additional research. Yet since measurement and sampling were held constant, and a strict translation procedure was applied, these differences may point to cultural patterns. Related, given the multiple comparisons across four countries, we recognize the risk of inflated Type I error. However, we are aimed at understanding how our model plays out within each national context, and thus, we treat country as an independent case.

Finally, our cross-country findings are limited to data from four countries only. This makes it notoriously difficult to statistically test the roles of macrolevel factors as well as the interaction of macrofactors and individual-level variables in a multi-level analysis. Still, we would argue that our data are by far superior to the stream of single-country studies, particularly well-studied Western countries.

7.3 | Future Research

We did not distinguish several types of uses, that is, the specific context and/or purpose of generative AI use. Also, the inclusion of additional predictors, such as individual difference variables

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or peer pressures, may lend deeper insights. Related, future research should explain why risk awareness does not appear to reduce usage intentions, as for instance, by theorizing aspects such as perceived usefulness, peer influence, or digital habits. Also, the different framings and understandings of generative AI risks by youth need more attention. Future research should also compare youth with adult populations, as the findings may look different for the latter. Even for youth, future research may expand the age range to identify generational differences. Importantly, future work should measure the actual generative AI literacy levels of youth, clearly separating perceived, self-ascribed literacy from actual competence. Finally, as generative AI becomes more embedded in all aspects of life, perceptions and behaviors may change, necessitating another fresh look.

7.4 | Implications and Conclusion

The findings of our study bear some important conclusions. The most important is that the perception of risks alone does not prevent young people from using generative AI. More specifically, information risks only predict the urge to regulate in one out of four countries, and more importantly, these risks were not dampening young individuals' intentions to use generative AI in the future. Social risks, by contrast, were strong and significant drivers of the urge to regulate in all countries, but again, they did not inhibit future usage intentions. Summarized in one sentence, young individuals may say, "Yes, there are risks, but I will use it anyway".

In terms of policy implications, the findings suggest that regulations need to be justified to youth stressing social risks, not only informational risks. If the discussion about policy regulation overemphasizes aspects such as misinformation, biases, or privacy, young individuals may not be persuaded by these aspects. They may rather respond to arguments related to their social relations and personal identity. Although we do not have data on this, we can speculate that policy regulations need to be tailored differently when targeting youth as compared with adults.

In terms of educational implications, educational programs about the various risks targeting young individuals may increase the awareness of the threats associated with generative AI, yet such information may not stop the youth from embracing this technology. This underlines the importance of real—rather than perceived—user competence with respect to generative AI. If young adults are willing to use generative AI, despite the risks, then a competent, balanced, and skillful use becomes extremely important. In a sense, this also means that although generative AI is here to stay with us, we need to equip young individuals with the necessary skill set to handle it thoughtfully and responsibly.

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Ethics Statement

This study was conducted in accordance with ethical standards and received approval from the IRB, Department of Communication at the University of Vienna (Confirmation Number: 993). Informed consent was obtained from all participants involved in the study.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data generated and analyzed are available under OSF https://osf.io/fmj3v/?view_only=2692e1a89b1e4271b226d5cad448198a.

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