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How do higher education students feel using ChatGPT? A multi-country survey on epistemic emotions and their antecedents

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ABSTRACT

Epistemic emotions concerning knowledge building or generation are important for higher education (HE) students, yet little is known about how they relate to generative artificial intelligence (AI). Guided by Pekrun's generalized Control-Value Theory (CVT), we examined epistemic emotions associated with ChatGPT use. The sample comprised 11,427 HE students representing 127 countries (based on self-reported citizenship), who completed an online survey. Structural equation modeling showed positive relations between ChatGPT use and ChatGPT control and value. ChatGPT control was positively related to curiosity and negatively related to surprise, enjoyment, anxiety, frustration, and boredom, whereas ChatGPT value was positively related to the three positive emotions and anxiety, and negatively related to the remaining negative emotions (i.e., confusion, frustration, and boredom). The model showed broad comparability across the gender, study field, and developmental-context groups represented in the sample, providing qualified support for the cross-group stability of the relations proposed by the CVT. A linear mixed model indicated that positive emotions were more frequent than negative emotions and identified modest differences across developmental contexts. Overall, these findings provide descriptive evidence of how ChatGPT use, control, and value are associated with HE students' epistemic emotions and may inform the future development and evaluation of educational practices, while not supporting causal or prescriptive policy conclusions.

1. Introduction

Epistemic emotions – i.e., those emotions related to knowledge acquisition – are a core element in students' knowledge building (Muis et al., 2018; Pekrun & Loderer, 2020), a critical resource for tackling the challenges of the globalized 21st-century society (Guo et al., 2022). The recent increasing attention paid to this type of academic emotions has revealed their key role in higher education (HE) students' motivation, metacognition, and learning outcomes, identifying also a range of relevant appraisals (Pekrun, 2024). However, to our knowledge, research has not yet explored the nature of these emotions connected with the global-spread conversational chatbot ChatGPT – the currently most popular interactive generative Artificial Intelligence (AI) system – targeting the population of HE students and examining their antecedents. The peculiar characteristics of interactions with ChatGPT – enabling the building of knowledge, scaffolding users' learning, and its worldwide adoption – make using ChatGPT a prototype task to investigate emotions associated with knowledge-building processes and products, while also examining whether their relations with theoretically relevant antecedents are comparable across different groups of students. Given the current massive and growing presence of AI technologies in HE learning contexts, shedding light on the nature of ChatGPT-related epistemic emotions and antecedents may contribute to a better understanding of students' learning and epistemic cognition – regarding "how people acquire, understand, justify, change, and use knowledge in formal and informal contexts" (Sandoval et al., 2016, p.

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457).

Although ChatGPT has spread rapidly across HE worldwide, countries differ considerably in their levels of generative AI adoption, digital infrastructure, educational technology integration, and institutional policies governing AI use in education. These contextual differences may shape students' experiences with ChatGPT. Accordingly, the present study draws on a multinational sample representing diverse citizenship backgrounds to examine individual students' epistemic emotions – rather than to compare national educational systems or AI policy environments.

Given the rapid integration of generative AI into HE learning contexts, it is particularly important to examine students' experiences at the initial stages of adoption. Although ChatGPT is already widely used for knowledge-related activities, empirical understanding of the emotional processes associated with its use remains limited. Investigating ChatGPT-related epistemic emotions during a relatively early phase can therefore provide a timely baseline for examining how students respond affectively to generative AI and for comparing these experiences with those emerging as AI systems, patterns of use, and institutional practices continue to evolve.

Against this background, this study addresses several interrelated gaps in the literature. First, despite the rapid adoption of generative AI in HE, little is known about the full range of positive and negative epistemic emotions that students experience when interacting with ChatGPT or about how these emotions relate to ChatGPT use, perceived control, and perceived value. Examining both positive and negative emotions offers a more comprehensive account of students' emotional experiences during generative AI-supported knowledge activities. Second, previous research has rarely applied the generalized CVT to interactions with generative AI or examined the theoretically proposed relations among ChatGPT use, control and value appraisals, and epistemic emotions. Although technology-acceptance frameworks are useful for explaining whether students intend to adopt and use generative AI, the generalized CVT is particularly well-suited to this research because it specifies how control and value appraisals are associated with discrete positive and negative emotions that arise during knowledge-related activities. In particular, limited evidence is available on whether control and value mediate the associations between ChatGPT use and students' epistemic emotions. Third, it remains unclear whether the measurement of the relevant constructs and the structural relations proposed by the CVT are comparable across students differing in gender, study field, and broader developmental context. Testing measurement and structural invariance across these groups can provide a more robust assessment of the model's comparability. Finally, much of the existing evidence on students' cognitive and emotional experiences with ChatGPT derives from single-country or comparatively restricted samples, limiting understanding of these processes across diverse backgrounds. By involving a very large sample of HE students representing 127 countries (based on self-reported citizenship), the present study provides timely cross-national evidence on ChatGPT-related epistemic emotions and their antecedents, while testing the robustness of the hypothesized model across multiple groups. To address these gaps, the present study responds to the following overarching research question: How and why do HE students from diverse national backgrounds experience epistemic emotions when using ChatGPT?

From an applied perspective, identifying how students' control and value appraisals are associated with positive and negative epistemic emotions may provide an empirical basis for educational institutions and policy makers to develop and evaluate practices that support more adaptive experiences with generative AI, while recognizing that the present cross-sectional findings do not establish causal effects or justify prescriptive policy recommendations.

2. Literature review

2.1. Epistemic emotions and the generalized Control-Value Theory

HE students feel a wide range of emotions while navigating everyday academic challenges. Such academic emotions, including the so-called epistemic emotions, play a paramount role in their well-being and learning (Pekrun, 2024).

According to theoretical approaches such as Pekrun's CVT (2006, 2024; Pekrun & Perry, 2014), academic emotions can be classified into at least four types: achievement emotions, topic emotions, social emotions, and epistemic emotions (Pekrun & Loderer, 2020). As is generally the case for all emotions, they can be differentiated based on various dimensions, including valence and arousal. The former distinguishes between positive or pleasant and negative or unpleasant emotions, while the latter between physiologically activating and deactivating emotions. The intersection of these two dimensions yields a four-quadrant representation of academic emotions.

Among the four types, achievement emotions are by far the most investigated, especially with HE students (Pekrun, 2024). They regard achievement activities (i.e., attending a lesson or studying) or outcomes (i.e., taking a test) – as their object focus – judged based on competence-related criteria. Topic emotions are prompted by the contents of learning materials, which become their object focus. Social emotions are connected to other individuals who play a role in the learning context, constituting their object of focus. Finally, epistemic emotions are those emotions related to knowledge building or generation. Their study is currently deemed a priority due to the exponential growth of the role of technology-mediated learning activities, such as those connected with generative AI, in schools and HE institutions.

In all tasks in which students develop knowledge, the fourth type of academic emotions, namely epistemic emotions, is likely to be present (Muis et al., 2018). The Greek-origin term "epistemic" traces back to the verb *epistanai*, i.e., "to know", indicating the processes of acquiring and mastering knowledge and competence. Going beyond the study of knowledge as "cold cognition", such processes are currently viewed as strictly related to emotions, shifting to a "hot cognition" approach, which also considers the affective components of epistemic cognition (Pekrun & Loderer, 2020). Epistemic emotions are defined as those emotions triggered by the knowledge-arising qualities of a cognitive task or activity (Brun et al., 2008; Muis et al., 2018; Pekrun & Loderer, 2020). In other words, they originate when individuals are somehow involved in knowledge-generation mechanisms. Their object focus comprises both the process of knowledge development and its product, i.e., knowledge itself (Pekrun et al., 2017). From an evolutionary perspective, we can assert that their purpose is to accompany individuals as they build knowledge about the external world and themselves, facilitating or constraining this process (Muis et al., 2018; Pekrun et al., 2017; Pekrun & Loderer, 2020).

Epistemic emotions result from continuous consideration of hypothesized and current progress toward an epistemic goal that can be impeded or achieved (Muis et al., 2018). They are typically prompted when discrepant or inconsistent information triggers cognitive incongruity or disequilibrium (D'Mello et al., 2014) as well as when consistent information causes a cognitive equilibrium (Muis, Pekrun, et al., 2015). Epistemic emotions can include the positive activating emotions of surprise (in some cases described as neutral or even negative), curiosity (sometimes defined also as negative), and enjoyment; the negative activating emotions of confusion and anxiety; and the negative deactivating emotions of frustration and boredom – even if frustration, being a combination of anger and sadness, also includes some activating characteristics (Pekrun, 2024).

The aforementioned incongruity can regard a conflict – or, conversely, the congruity can refer to consistency – between different pieces of knowledge concerning also different temporal frameworks: for example, between fragments of previous and current knowledge, or between fragments of existing knowledge (Muis et al., 2018; Pekrun et al., 2017; Pekrun & Loderer, 2020), clearly resembling the Piagetian *socio-cognitive conflict* (Mugny & Doise, 1978). If we consider a student-chatbot interaction from the very beginning, for example, the incongruity between prior knowledge, expectations, or beliefs and new knowledge can give rise to surprise. Curiosity can arise from a desire to know something unknown in such an uncertain situation, filling the perceived gap between current and future knowledge. Confusion can emerge when students are aware of incongruities that are far from a solution, for example in complex learning tasks for which they choose to be assisted by a chatbot. If the situation is particularly uncertain and students' need for closure (i.e., a motivational propensity to get an answer to bypass ambiguity; Kruglanski, 2013) is high, such discrepancies could also trigger anxiety. Finally, enjoyment, on the one hand, and frustration and boredom, on the other hand, can co-occur with the previous emotions, in case the process of knowledge development is experienced, respectively, as pleasant or unpleasant. However, they can also appear at the end of such a process, when incongruities are resolved or seem impossible to resolve. It is noteworthy that while some emotions, such as curiosity or confusion, are inherently epistemic, others, such as enjoyment or anxiety, can also be classified as achievement emotions; therefore, epistemic emotions share characteristics with other types of academic emotions (Pekrun et al., 2017).

Beyond incongruity, also novelty and complexity of the information, and achievement or impasse in reaching epistemic goals – all elements that can be salient when students interact with ChatGPT – can be antecedents of epistemic emotions (Muis et al., 2018), together with the two proximal antecedents of emotions conceptualized at the core of the CVT, control and value beliefs. This list of antecedents, however, may not be exhaustive (Muis et al., 2018).

In the last two and a half decades, extensive literature has demonstrated how achievement emotions are connected with various correlates for students from primary schools to HE institutions. Most research has referred to Pekrun's CVT of achievement emotions (2006; Pekrun & Perry, 2014), which has recently been reformulated as the generalized CVT to include achievement, social, epistemic, and existential emotions – whose object focus is health, life, disease, and death (Pekrun, 2024). However, despite the current relevance of epistemic emotions for learning processes and products, their correlates have been investigated far less than those of achievement emotions, particularly in the context of naturalistic, everyday learning tasks involving technology.

According to the generalized CVT, academic emotions can be conceptualized in terms of their reciprocal interrelations with a range of antecedents and consequences, with the theory proposing that the basic functional relations may show substantial consistency across persons and contexts (Pekrun, 2006, 2024; Pekrun & Perry, 2014). Acknowledging the existence of a variety of mechanisms influencing emotions, spanning from genetic dispositions to sensory perceptions, this approach emphasizes the role of cognitive appraisals, such as perceived control and value, in the generation process of education-relevant emotions (Pekrun, 2024). This is based on the assumption that such emotions arise in contexts shaped by culture and civilization, and are given meaning primarily through adaptive interpretations of the environment and one's capacities to cope with it. Thus, although the CVT proposes a degree of cross-context consistency in the relations between academic emotions – including epistemic emotions – and their correlates, it also posits that the frequency and intensity of these emotions can vary according to the characteristics of persons and contexts (Pekrun, 2024). For example, Raccanello et al. (2022) reported that in a sample of more than 17,000 HE students, e-learning-related achievement emotions varied across personal and contextual factors. While usually positive achievement emotions are more frequent than negative ones (e.g., Raccanello et al., 2021), in that case the negative emotions prevailed – nevertheless, this could be attributed to the COVID-19 context in which the data were gathered – for females (and not for males), and only in two study fields out of four (in natural and life sciences, arts and humanities, and not in social sciences and applied sciences). However, knowledge of the variability of epistemic emotions across factors such as gender, study field, or country, based on large cross-cultural samples of HE students, remains limited. In a study that, with a more reduced sample, examined gender, the authors reported no significant differences in control, value, and epistemic emotions (Muis, Psaradellis, et al., 2015). In another one focused on the development of a scale assessing seven epistemic emotions (i.e., the Epistemically-Related Emotion Scale, ERES; Pekrun et al., 2017), the authors demonstrated that the scale structure was invariant at the metric level across students from the United States, Canada, and Germany – but epistemic emotions' rates were not compared among countries.

According to the generalized CVT (Pekrun, 2006, 2024; Pekrun & Perry, 2014), the main antecedents of academic emotions are perceived control and value beliefs, which are considered proximal appraisals. They are, in turn, influenced by more distal individual (such as gender) and contextual antecedents (such as scaffolding by teachers, virtual agents, or autonomy support). In brief, academic emotions arise when students perceive that they do or do not control learning activities or results that they deem relevant. For epistemic emotions (Muis et al., 2018), perceived control refers to expectations about one's own controllability of epistemic-related actions and outcomes, such as beliefs about a student's ability to comprehend a particular concept. Perceived value refers to the subjective relevance of an epistemic activity or outcome, and can be characterized by an intrinsic value – i.e., when students are interested or give importance to activities or outcomes – and an extrinsic value – i.e., when students identify positive consequences of activities or outcomes, such as for everyday life.

A large amount of research supported CVT's assumptions about the positive and negative relations, respectively, between control and value on the one hand and positive and negative achievement emotions on the other hand, with the exception of anxiety arousing with low control and high value (Pekrun, 2024; Pekrun & Loderer, 2020). Nevertheless, these issues have been examined less frequently for epistemic emotions, with some exceptions focused on science, technology, engineering, and mathematics (STEM) disciplines (Dowd et al., 2015; Muis, Psaradellis, et al., 2015; Munzar et al., 2021; Pekrun et al., 2017; Schubert et al., 2023). Muis, Psaradellis, et al. (2015) documented that the more fifth-graders controlled their mathematics abilities, the less they experienced confusion and anxiety during problem-solving; the more they valued mathematics, the more they experienced curiosity and enjoyment, and the less they felt confusion, anxiety, frustration, and boredom. Similar results were reported by Munzar et al. (2021) with third-to sixth-graders, always about mathematics problem-solving. About HE, Dowd et al. (2015) found that university students' self-efficacy and confidence in reasoning were negatively related to their confusion while reading new materials before introductory physics course lessons. While developing the ERES with university students, Pekrun et al. (2017) found that task value correlated positively with curiosity and enjoyment, and negatively with boredom, when reading texts containing conflicting information about climate change. Schubert et al. (2023) showed that HE students' subjective control and value in a mathematics proof-construction task were positively related to curiosity and enjoyment; for negative emotions, value was negatively related to boredom (but not to confusion or frustration). In summary, previous findings indicate that students' control and value beliefs are positively related to positive epistemic emotions, such as curiosity and enjoyment, and negatively related to negative epistemic emotions, such as confusion, anxiety, frustration, and boredom, with some exceptions. It is worth reporting that data from more than half a million 15-year-olds from 72 countries (PISA 2015 database) indicated that both science self-efficacy, on the one hand, and utility and intrinsic value, on the other hand, were higher for students with more adaptive beliefs about knowledge, conceptualizing it as changeable (Guo et al., 2022).

In turn, academic emotions impact students' performance directly and through the mediation of cognitive, metacognitive, and motivational processes. Numerous studies have demonstrated that these relations characterize HE students, particularly regarding achievement emotions (Pekrun, 2024). However, the influence of epistemic emotions remains somewhat underexplored. Muis et al. (2018) described four possible outcomes of epistemic emotions, for: (a) planning and goal setting – negatively predicted by primary students' surprise (fostering confusion) and boredom (Muis, Psaradellis, et al., 2015); (b) cognitive and metacognitive strategies – with HE students' critical thinking, knowledge elaboration, and rehearsal predicted by curiosity felt while reading contradictory texts on climate change, among a total of seven epistemic emotions (Chevrier et al., 2019); (c) motivation – with HE students' enjoyment and curiosity about mathematics proof construction mediating the relation of control and value with intrinsic motivation (Schubert et al., 2023); and (d) learning outcomes – with some metacognitive strategies or motivational constructs (see points b and c) impacted by the aforementioned emotions influencing in turn math performance or text comprehension (Chevrier et al., 2019; Muis, Psaradellis, et al., 2015; Schubert et al., 2023). To sum up, previous literature (as revised by Schubert et al., 2023) suggests that positive epistemic emotions such as curiosity and enjoyment should impact performance favorably, while surprise could have both positive and negative effects (Chevrier et al., 2019), being a precursor of curiosity and confusion (Vogl et al., 2019). Among negative epistemic emotions, confusion can foster engagement only if the situation is perceived as resolvable – otherwise, it would impair it (Muis, Psaradellis, et al., 2015) and anxiety and boredom are generally documented to be detrimental (Chevrier et al., 2019; Schubert et al., 2023).

2.2. Higher education students interacting with ChatGPT: use, control, value, and affect

Most studies on academic emotions have explored learning processes related to single representations, such as learning from a single text or a single viewpoint (Pekrun & Loderer, 2020). Nevertheless, the most recent technological developments compel scientists to disentangle the relations between academic emotions and their correlates in multi-representation and multi-perspective learning tasks. Interacting with ChatGPT offers a prominent example of such tasks, triggering epistemic emotions typically associated with knowledge generation while activating cognitive activities involved in knowledge acquisition and exploration (Vogl et al., 2019). However, using ChatGPT does not constitute an epistemic activity merely because the system generates information. Its epistemic character depends on the object focus and goal of the interaction. ChatGPT use may be epistemic when students formulate knowledge-related questions, seek explanations, compare generated information with prior knowledge or expectations, detect inconsistencies, revise their understanding, or evaluate the adequacy of the output. In these cases, ChatGPT functions as the medium of the activity, whereas the emotion is directed toward the knowledge-building process or product. Conversely, emotions primarily driven by usability, technical failures, response speed, or access to the system would be better characterized as technology-use emotions.

ChatGPT, as the leading chatbot in AI large language models (LLMs), is driving a major shift in current paradigms of information acquisition (Abbas et al., 2024). It is an intelligent chatting robot capable of handling complex conversations with its users and understanding and responding to instructions and prompts in a nearly human-like manner (Wu et al., 2023). Developed by OpenAI, this chatbot was first released publicly in November 2022 and reached more than 100 million active users within two months (Wu et al., 2023). Unlike traditional AI models, generative AI, such as ChatGPT, does not simply detect patterns and make predictions; instead, it creatively produces new outputs, leveraging billions of parameters (OpenAI, 2025).

Epistemic emotions triggered by the use of ChatGPT can have both similarities and differences compared to those aroused in the zone of proximal development (ZPD) in other learning tasks, such as face-to-face interactions or online collaborative environments (typically studied by Computer-Supported Collaborative Learning, CSCL, approaches; Cress & Kimmerle, 2023; Ghazal et al., 2020). First, as for learning occurring within the ZPD with a human expert, also in the interaction between a student and a chatbot, there is an entity with more expertise (i.e., ChatGPT) offering on-demand and personalized tutoring (Farrokhnia et al., 2024; Ravšelj et al., 2025) and an entity with less expertise (i.e., the student), and the process is aimed at learning through co-joint actions. Users can ask any question, receive a written answer, and then rephrase and refine their previous questions, engaging in an almost-human conversation in which the chatbot learns from both its massive database and users' reactions. Second, ChatGPT's knowledge, built on a vast repository of dynamic information updated based on individuals' utterances, can be considered similar to knowledge developed through collaborative efforts among people (Cress & Kimmerle, 2023). Third, using ChatGPT can facilitate the transition from the knowledge-telling writing typical of novices to the knowledge-transforming writing characteristic of experts (Scardamalia & Bereiter, 1987). Nevertheless, there are at least three evident differences we can draw on to support the relevance of studying epistemic emotions in the unique setting of interacting with ChatGPT. First, being ChatGPT a non-human entity – with the advantage of being perceived as always available and guaranteeing real-time and continuous support (Farrokhnia et al., 2024; Ravšelj et al., 2025) – there is the possibility of an overwhelming sense of loss and helplessness if it is not present, even for trivial connecting problems. Second, ChatGPT lacks the ability to infer knowledge about the context (Cress & Kimmerle, 2023), prompting a variety of affective reactions during knowledge building that depend on the coherence between its answers and the environment. Third, the final objective of the interaction does not include the learner's autonomy in the knowledge-building process. Rather, there is a risk of the latter's overdependence on ChatGPT (Farrokhnia et al., 2024), which undermines self-determination and the sense of autonomy so crucial for learning (Ryan & Deci, 2020), and possible influences on connected affective reactions. Therefore, ChatGPT-related epistemic emotions could have peculiar task-based characteristics that make the ChatGPT context worth exploring.

Moreover, being free, worldwide available, and very easy to use compared to other digital technologies (Cress & Kimmerle, 2023; Grassini et al., 2024), ChatGPT is an ideal tool to be investigated, focusing on samples of students differing in a variety of personal and cultural characteristics, for example, about their gender, study field, and country development. Therefore, studying ChatGPT-related epistemic emotions allows us to examine whether the relations proposed by the generalized CVT (Pekrun, 2024) show comparability across students with different personal and developmental backgrounds, while also responding to the need for region-specific research on factors associated with ChatGPT use, which may depend on the level of technology adoption across countries (Grassini et al., 2024).

Parallel to the explosion of research on the opinions of teachers and experts regarding the potential of ChatGPT use for HE learning and teaching (e.g., Ali et al., 2024; Farrokhnia et al., 2024; Sallam et al., 2023), an emergent line of studies is taking the perspective of students (Abbas et al., 2024; Abdaljaleel et al., 2024; Boubker, 2024; Bouteraa et al., 2024; Galindo-Domínguez et al., 2025; Grassini et al., 2024; Leite, 2025; Lo et al., 2024; Ofosu-Ampong et al., 2023; Oubibi et al., 2025; Ravšelj et al., 2025; Strzelecki, 2023; Tiwari et al., 2024; Wu et al., 2024; Yilmaz et al., 2023).

Rates of self-reported HE students' use of ChatGPT, as reported in a few cross-cultural studies on this issue, range from approximately 53% to 71% (Abdaljaleel et al., 2024; Ravšelj et al., 2025). A previous study involving the same cross-cultural sample as this research found that HE students primarily use ChatGPT for brainstorming, summarizing texts, simplifying complex knowledge, searching for research articles, and occasionally for professional and creative writing (Ravšelj et al., 2025). Nevertheless, ChatGPT's perceived reliability was lower for providing information and favoring classroom learning, and the need for regulations became evident. The participants also believed that the use of ChatGPT could improve their learning and achievement, with knowledge-field differences: more for informatics-related abilities, such as AI literacy, digital communication, and content creation skills, and less for native language proficiency, numeracy, and soft skills like interpersonal communication, decision-making, and critical thinking. Additionally, ethical concerns arose, despite other evidence suggesting that potential negative outcomes, such as plagiarism, may be more closely related to a culture of cheating or amotivation than to the use of ChatGPT (Galindo-Domínguez et al., 2025). Some studies have also documented negative academic consequences, such as increased procrastination, memory loss, and poorer performance (Abbas et al., 2024); however, research on ChatGPT's impact on learning is still in its early stages.

Many of the few studies that explored ChatGPT use considered the Technology Acceptance Model (TAM; Davis, 1989; Granić & Marangunić, 2019) and its subsequent versions, such as the Extended Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2012), as the main theoretical frameworks, usually administering online surveys. The TAM includes two main predictors of users' acceptance and use of technology, i.e., perceived ease of use – referring to the needed effort – and usefulness; two constructs quite similar, respectively, to perceived control and value as conceptualized by the CVT. However, related evidence about ChatGPT is currently inconsistent.

Although TAM and the generalized CVT share an emphasis on users' cognitive evaluations, their constructs have only partial conceptual overlap. Perceived ease of use and perceived control both concern whether engagement with a system or activity is experienced as manageable. However, perceived ease of use refers specifically to the degree of effort required to use a technology, whereas perceived control in CVT concerns the broader perceived controllability of an activity and its outcomes, including students' beliefs that they can successfully manage knowledge-related actions. Similarly, perceived usefulness and perceived value both concern the perceived relevance or benefits of an activity. Nevertheless, perceived usefulness is primarily defined in instrumental terms, referring to the extent to which using a technology is expected to improve performance, whereas value in CVT is broader and includes intrinsic interest, subjective importance, and utility.

The two frameworks also differ in their principal explanatory targets. TAM was developed primarily to explain technology acceptance, behavioral intention, and actual use. The generalized CVT, instead, explains the generation of academic emotions by specifying how control and value appraisals relate to discrete positive and negative emotions and, in turn, to learning-related processes and outcomes. Therefore, TAM is useful for contextualizing previous findings on students' acceptance and use of ChatGPT, but it does not by itself provide a sufficiently differentiated account of epistemic emotions. In the present study, CVT was selected as the principal theoretical framework because the primary focus is on discrete emotions arising during ChatGPT-supported knowledge activities, rather than on acceptance of or intention to use the technology.

HE students' ChatGPT ease of use resulted in some cases low – with Omani students highlighting the corresponding mental effort together with doubts about positive effects on their skills (Tiwari et al., 2024) – and in others high – for example, with Polish students appreciating ChatGPT's conversational style (Strzelecki, 2023) and in a five-country sample (Abdaljaleel et al., 2024). Models testing whether it predicted the behavioral intention to use ChatGPT reported nonsignificant relations – with Norwegian (Grassini et al., 2024), Omani (Tiwari et al., 2024), and Polish (Strzelecki, 2023) HE students – documenting also the lack of a moderation effect by gender (Grassini et al., 2024). Considering the impact of control on use, and involving a six-country sample of students of non-science majors, Bouteraa et al. (2024) found that educational and technological self-efficacy (together with personal anxiety) positively impacted ChatGPT use. Similarly, interventions using different AI-integrated tools (including ChatGPT) or a ChatGPT-based Intelligent Learning Aid resulted in improvements in HE students' writing and general self-efficacy, respectively (Oubibi et al., 2025; Wu et al., 2024). So, data on ChatGPT control, in terms of ease of use or self-efficacy, are currently mixed and warrant further attention.

ChatGPT usefulness, instead, is generally high, as perceived by students from Egypt, Ghana, Iraq, Kazakhstan, Kuwait, Lebanon, Jordan, Oman, and Poland involved in different HE study fields (Abdaljaleel et al., 2024; Ofosu-Ampong et al., 2023; Strzelecki, 2023; Tiwari et al., 2024; Yilmaz et al., 2023). This is also testified by the variety of learning-related functions identified by HE students for ChatGPT (e.g., Ravšelj et al., 2025). Moreover, the impact of ChatGPT usefulness on acceptance of or intention to use ChatGPT is generally positive (Ofosu-Ampong et al., 2023; Tiwari et al., 2024; Yilmaz et al., 2023). However, whether the opposite relation is impactful remains unclear.

Within the generalized CVT, perceived control and value are conceptualized as proximal cognitive appraisals involved in the generation of academic emotions, including epistemic emotions. In the present context, ChatGPT control concerns students' perceived capacity to manage their interaction with the system, whereas ChatGPT value concerns the interest, importance, and utility they attribute to its use. ChatGPT use is treated as a more distal behavioral variable that may be associated with these appraisals: more frequent interaction may be accompanied by greater familiarity with ChatGPT and students' perceived control over its use, while also being associated with stronger perceptions of its relevance and utility. Control and value, in turn, are expected to be associated with the positive and negative epistemic emotions experienced when students use ChatGPT for knowledge-related activities.

Some studies have also begun to explore the affect associated with ChatGPT, based on different theoretical assumptions and methodologies. Using sentiment analysis on 1.1 million tweets sent between December 2022 and June 2023, Demirel et al. (2025) described public perception of ChatGPT across six continents as positive in approximately half of the tweets (more frequent in low-income countries), with the remaining tweets neutral or negative. Focusing on HE faculties and using the same technique, Mamo et al. (2024) revealed that, out of a total of 3559 comments about ChatGPT published between November 2022 and April 2023, 40% were positive, 51% neutral, and 9% negative. Trust and joy prevailed among positive sentiments, while fear and anger among the negative ones. Considering HE students' emotions, a systematic review of 72 articles published within one year after ChatGPT's release indicated that its use in learning contexts triggered mixed emotions: engaging, such as satisfaction, interest, or fun, and disengaging, such as disappointment, worry, or anxiety – however, most studies were of short duration (Lo et al., 2024).

As regards factors associated with ChatGPT emotions, studies using the TAM reported inconsistent results about hedonic motivation – i.e., the fun or pleasure associated with using technology – which is usually a factor influencing the behavioral intention to use technology. Hedonic motivation did (Strzelecki, 2023; Tiwari et al., 2024) or did not significantly impact HE students' intention to use ChatGPT (Grassini et al., 2024), respectively, in early or later phases of ChatGPT's release – and novelty rather than customization were proposed as explaining dimensions (Strzelecki, 2023). Moreover, HE students' satisfaction with ChatGPT was predicted by both ease of use and usefulness (Boubker, 2024). Some studies indicated a reduction in HE students' anxiety when using ChatGPT, due to the low-pressure context, but in others, worry emerged about ethics-related concerns (Lo et al., 2024). Abdaljaleel et al. (2024) documented that ChatGPT-related anxiety – generally low – of a five-country sample of HE students did not differ according to ChatGPT use, gender, university (private or not), or nationality. Finally, a systematic review and meta-analysis on chatbot effectiveness (Abd-Alrazaq et al., 2022) showed inconsistent and scant evidence on the impact of chatbots on stress, anxiety, depression, or well-being, pointing to the need for research disentangling the factors responsible for such relations, i.e., focusing on specific tasks (e.g., using a chatbot with definite characteristics) and affective constructs (e.g., narrowing down the study to one emotion type).

Taken together, previous research indicates that ChatGPT is increasingly used for knowledge-related activities in HE and that students' experiences may involve both positive and negative affective responses. However, existing studies have primarily focused on technology acceptance, general affect, or restricted samples, leaving unclear how ChatGPT use, control, and value are jointly associated with discrete epistemic emotions. The generalized CVT provides an appropriate framework for addressing this gap because it specifies the role of control and value appraisals in the generation of academic emotions. Building on this theoretical and empirical background, the following section presents the aims, hypotheses, and conceptual model of the current study.

2.3. The current study

We explored how and why HE students feel epistemic emotions when using ChatGPT during its early release stages, involving participants representing 127 countries (based on self-reported citizenship). Although these participants came from diverse national backgrounds, the study focuses on individual-level processes rather than comparisons between countries with different AI adoption levels or HE policies. The study was included in a larger project entitled "Students' Perception of ChatGPT" (https://www.covidsoclab.org/chatgpt-student-survey/), promoted by the University of Ljubljana, Slovenia, and involving international partners. Through an online survey, the project aimed to investigate HE students' perceptions of their experience with ChatGPT from October 2023 to February 2024. The survey was completed by more than 23,000 HE students from more than 100 countries (Ravšelj et al., 2025). It comprised 42 questions that explored sociodemographic characteristics and aspects concerning ChatGPT, including usage, capabilities, regulation, ethical concerns, affective dimensions, and educational and job-related issues.

To our knowledge, no previous study has examined students' epistemic emotions related to ChatGPT and their antecedents, particularly involving a very large sample of HE students from different countries. Nevertheless, using an instrument such as ChatGPT exemplifies most of the key characteristics of typical tasks in which epistemic emotions arise. The internationally diverse composition of the sample also enabled us to examine whether the measurement properties and structural relations proposed by the CVT were comparable across students differing in gender, study field, and broader developmental context. Moreover, we had the opportunity to explore whether and how the rates of these emotions varied according to the aforementioned parameters. Given that ChatGPT became available to the general public in November 2022, our survey can be considered a milestone for exploring students' epistemic emotions in this early phase and for comparing them with those characterizing future phases, in which students' experiences when interacting with a conversational AI chatbot may be highly diverse.

2.3.1. Aim 1

Based on the CVT, we tested a model in which ChatGPT use was associated with beliefs about ChatGPT control and value, in turn associated with epistemic emotions (Fig. 1). In line with the generalized CVT, higher perceived control and value were generally expected to be associated with more frequent positive epistemic emotions and less frequent negative epistemic emotions. Anxiety represents a theoretically relevant exception because it may arise when an activity or outcome is highly valued but perceived control is low. The hypothesized model examines both the direct relations of ChatGPT use with epistemic emotions and the indirect relations operating through perceived control and value.

Hypothesis 1a. We hypothesized that ChatGPT use was related to the proximal antecedents (ChatGPT control, ChatGPT value) of epistemic emotions. We expected that students who reported using ChatGPT more frequently would perceive greater control over its use and attribute to it a higher value in terms of interest, importance, and utility. Conversely,

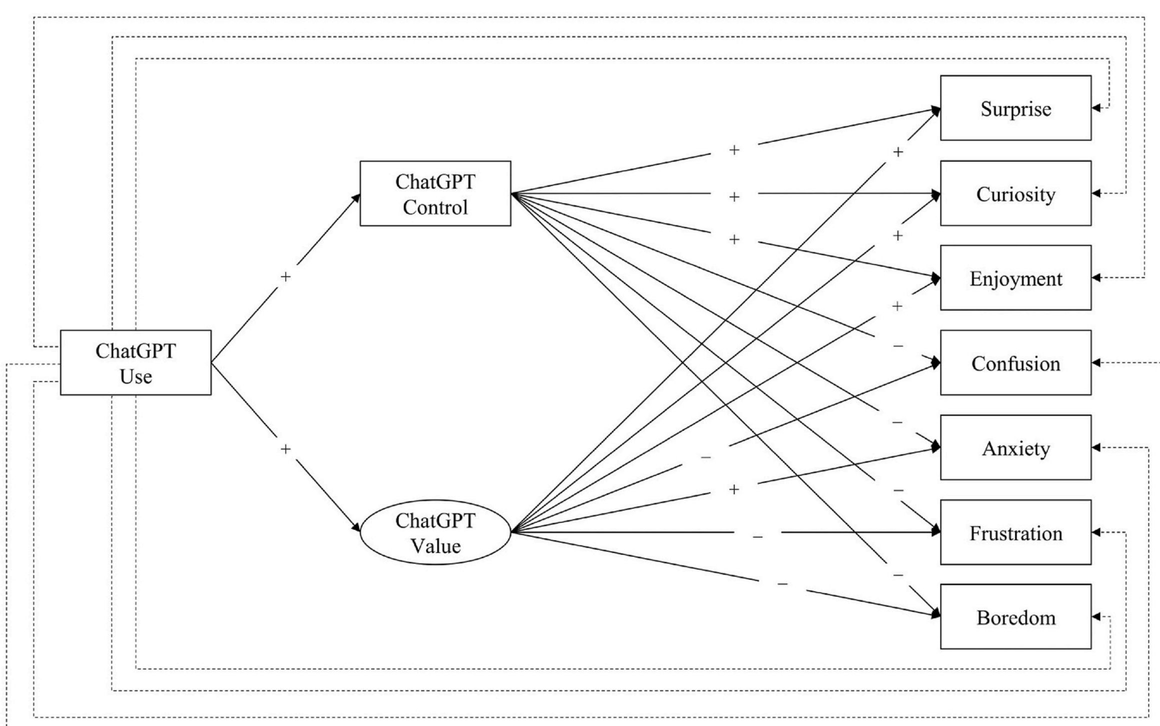

Fig. 1. Conceptual model of the relations between ChatGPT use, proximal antecedents (ChatGPT control and ChatGPT value), and epistemic emotions (surprise, curiosity, enjoyment, confusion, anxiety, frustration, and boredom). Dashed lines represent paths for which no specific hypotheses were formulated.

we expected that students using it less frequently would have lower levels of control and value.

Hypothesis 1b. We hypothesized that ChatGPT control and value were associated with ChatGPT-related epistemic emotions. Students with higher control and value were expected to feel more frequently positive epistemic emotions (i.e., surprise, curiosity, and enjoyment) and less frequently negative epistemic emotions (i.e., confusion, frustration, and boredom), with the exception of anxiety, for which lower control and higher value were expected to be associated with higher scores, in line with results typical of achievement emotions.

Hypothesis 1c. We hypothesized that ChatGPT control and value mediated the relation between ChatGPT use and ChatGPT-related epistemic emotions. Considering the absence of previous data on this issue, we explored whether use was directly or indirectly associated with epistemic emotions through control and value.

2.3.2. Aim 2

We investigated the model's invariance across gender, study field, and cultural context to examine whether the measurement properties and structural relations were comparable across the groups represented in the sample.

Hypothesis 2. We expected the measurement and structural models to show broad comparability across gender, study field (arts and humanities, social sciences, applied sciences, and natural and life sciences), and cultural context.

2.3.3. Aim 3

We focused on ChatGPT-related epistemic emotions. We investigated differences in their mean scores, taking into account gender, study field, and cultural context. This aim was exploratory, and we did not formulate any specific hypothesis.

3. Method

3.1. Participants

We involved a convenience sample including 11,427 students enrolled in HE institutions, at least 18 years old (M = 22.902 years, SD = 6.122, Mdn = 21.000, interquartile range = 3.000 years; 55% females, 45% males). Most of them were studying full-time (87%). The students were attending undergraduate (84%) or postgraduate courses – master's (12%) and doctorate courses (4%). Their study fields were arts and humanities (12%), social sciences (41%), applied sciences (36%), and natural and life sciences (11%). Participants reported citizenship from 127 countries, while 16 respondents selected the category "Other", resulting in 128 response categories overall. To characterize the broader developmental context of participants' countries of citizenship, countries were classified according to the Human Development Index (HDI; United Nations Development Programme, n.d.). HDI was selected because it provides a standardized composite indicator of education, health, and income, allowing the sample to be described across varying levels of human development rather than as a direct measure of cultural differences. Based on this classification, 5% of participants were from countries with low HDI, 7% from countries with medium HDI, 42% from countries with high HDI, and 46% from countries with very high HDI (see Table A of the Supplementary Materials, SM, for the list of countries and the number of participants per country, and Table B for descriptive statistics by HDI). The participants reported that, during the semester in which they completed the survey, they were studying in 89 different countries. This sample is a sub-sample of Ravšelj et al. (2025) study, including only students who reported using ChatGPT (71% of the initial sample) and provided complete responses on the socio-demographic data, ChatGPT use, control, value, and epistemic emotions. Because recruitment relied on a convenience sampling strategy through participating HE institutions, the number of participants varied across countries. Consequently, the sample was intended to provide broad international diversity rather than nationally representative country samples, and the findings should be interpreted at the individual rather than the country level.

3.2. Procedure

This study employed a cross-sectional research design to examine ChatGPT-related epistemic emotions and their antecedents among HE students from multiple countries through an online survey. This project is in line with the Declaration of Helsinki about research on human participants and with the American Psychological Association (APA) ethical standards. It was approved by the ethical committees of several HE institutions, i.e., the University of Oran 1, Algeria (Ethical Clearance Number, ECN: 03/CED/FACMED/2023); the University of Nicosia and the European University Cyprus, Cyprus (ECN: EEBK EII 2023.01.318); the Polytechnic University, Ecuador (ECN: C-22); the University of Verona, Italy (ECN: 2023_25); Yamanashi Gakuin University, Japan (ECN: 23–010); the University of Luxembourg, Luxembourg (ECN: ERP 23–101 StuPer ChatGPT SA/cd); Imam Abdulrahman Bin Faisal University, Saudi Arabia (ECN: IRB-2024-02-091 and IRB-2024-10-316); the University of Chester, United Kingdom (ECN: ASCHPR0211/23); and the University of East London, United Kingdom (ECN: ETH2324-0028).

We recruited participants using a convenience sampling strategy to obtain a large, internationally diverse sample of HE students, in collaboration with international project partners. The survey was disseminated through the communication systems of the participating HE institutions by the international project partners, who invited eligible students to participate. Participants provided informed consent for participation and data processing after reading the informed consent form, which specified that participation was anonymous and voluntary and that they could withdraw at any time without consequence. The questionnaire was developed in English and subsequently translated into Arabic, Hebrew, Italian, Japanese, Spanish, and Turkish by native speakers proficient in English. The survey was administered via the 1 KA (One Click Survey; https://www.1ka.si/d/en) web application between 9 October 2023 and 29 February 2024.

3.3. Measures

We focused on 10 questions for a total of 18 items, concerning socio-demographic data – with one single item each (i.e., one question for gender, study field, study level, study status, and two questions for cultural context); ChatGPT use (one question with one single item); proximal antecedents (one question with one single item for control and three items for value); and epistemic emotions (one question with seven single items). The questions and items considered in this study are reported in Table C of the SM.

Although single-item measures do not permit assessment of internal consistency or factorial structure and are therefore psychometrically less robust than multi-item scales, they can be appropriate when constructs are narrowly defined and easily understood. Their use was also intended to reduce respondent burden and cognitive fatigue in this large-scale, multilingual survey covering several domains (e.g., Raccanello et al., 2022; Raccanello et al., 2024).

3.3.1. Socio-demographic data

Gender. Students specified their gender (*What is your gender?*) as *male*, *female*, or *other gender identity*; they were also allowed to report that they preferred not to respond.

Study Field. Students indicated their main field of study (*Which is your main field of study?*), choosing among arts and humanities (history and archaeology, languages and literature, philosophy, and ethics and religion), social sciences (public administration, economics, business, law, educational science, sociology, and psychology), applied sciences (computer science, information technology, civil engineering and geodesy, mechanical engineering, sport, medicine, and healthcare), and natural and life sciences (electrical engineering, biotechnical, pharmacy, chemistry, and mathematics and physics). They also reported their study status (*What is your student status?*), full-time or part-time, and the level of study they were enrolled in (*What level of study are you enrolled in?*), undergraduate or postgraduate (master's or doctoral) degree.

Cultural Context. Students indicated both their citizenship (*What is your citizenship?*) and the country where they were studying during the semester in which they completed the survey (*In which country are you studying this semester?*), choosing from a list of 197 countries (including the category *Other*). We further coded the response about the citizenship according to countries' HDI (United Nations Development Programme, n.d.), a 4-level composite index (1 = *low HDI*, values 0–.549; 2 = *medium HDI*, values .550–.699; 3 = *high HDI*, values .700–.799; and 4 = *very high HDI*, values .800–1.000) combining a health dimension (in terms of life expectancy at birth), an educational dimension (in terms of expected years of schooling and mean years of schooling for older than 25-year-olds), and an economic dimension (in terms of gross national income per capita). The most recent available data are related to 2022.

3.3.2. ChatGPT use

We assessed students' use of ChatGPT using one ad hoc item (*To what extent do you use ChatGPT in general?*), similar to other studies (Abbas et al., 2024; Galindo-Domínguez et al., 2025). The students responded on a 5-point scale (1 = *rarely* and 5 = *extensively*).

3.3.3. Proximal antecedents

The students evaluated the proximal antecedents of epistemic emotions on a 5-point scale (1 = *strongly disagree* and 5 = *strongly agree*), indicating how much they agreed with each item. Alternatively, they could also choose a sixth response (*no opinion*). All the items were adapted to refer to ChatGPT.

ChatGPT Control. To measure ChatGPT control, we used one item (*I have the impression that using ChatGPT is under my control*) adapted from Goetz et al. (2010). Single-item measures to assess perceived control were also used in previous research (Jarrell et al., 2016; Tong et al., 2005).

ChatGPT Value. To assess ChatGPT value, we used three items measuring interest (*Using ChatGPT is interesting to me*), importance (*Being able to use ChatGPT is important to me*), and utility (*ChatGPT can help with things in everyday life*) of using ChatGPT, adapted from previous works (Goetz et al., 2010; Muis, Psaradellis, et al., 2015; Putwain et al., 2018). We calculated Cronbach's (1951) alpha (α) and McDonald's (1999) omega (ω; cutoff for good reliability: α/ω > .70; psych package, Revelle, 2024). For this scale, reliability was adequate, with α/ω = .748/.751.

3.3.4. Epistemic emotions

We utilized the seven-item brief version of the ERES (Pekrun et al., 2017). The participants rated the frequency with which they usually feel seven emotions when using ChatGPT (*How often do you feel the following emotions while using ChatGPT?*) on a 5-point scale (1 = *never* and 5 = *always*). They could again choose a sixth option (*no opinion*). The brief ERES includes seven adjectives related to three positive epistemic emotions, i.e., surprise, curiosity, and enjoyment (*surprised, curious,* and *excited*), and four negative epistemic emotions, i.e., confusion, anxiety, frustration, and boredom (*confused, anxious, frustrated,* and *bored*). Academic emotions have already been assessed through single-item measures (D'Mello & Graesser, 2012; Raccanello et al., 2022).

3.4. Data Analysis

We utilized the R software (Version 4.5.0; R Core Team, 2025). The analyses were conducted on the final cleaned dataset of 11,427 participants, all of whom provided complete data on the variables examined. Prior to the analyses, the dataset was screened for eligibility and completeness. The sample included only participants who reported using ChatGPT and provided complete responses on the variables required for the analyses. Overall, 20 cases were excluded because of incomplete data. No imputation was performed. No additional formal screening for duplicate submissions, careless responding, or implausible response patterns was conducted, as the anonymous survey design and the information available in the dataset did not allow such screening to be performed reliably.

Concerning the first aim, a structural equation modeling (SEM) approach was selected because the analysis involved a system of simultaneous relations among ChatGPT use, control, value, and multiple epistemic emotions (surprise, curiosity, enjoyment, confusion, anxiety, frustration, and boredom), including both direct and indirect associations. SEM was particularly appropriate because it allowed us to estimate the measurement component of ChatGPT value and the structural paths within a single model, while accounting for measurement error in the latent value construct. It also enabled the simultaneous estimation of the seven emotion outcomes and the decomposition of the associations between ChatGPT use and emotions into direct, specific indirect, total indirect, and total effects. Because all observed variables included in the SEM were measured using ordered five-point response scales, we used the diagonally weighted least squares estimator (DWLS; lavaan package, Rosseel, 2012), which is suitable for models including ordinal observed variables. Before estimating the structural relations, we separately evaluated the measurement model for ChatGPT value through a one-factor confirmatory factor analysis (CFA). The CFA included the three ordinal indicators of intrinsic value, importance value, and utility value, and was estimated using the same DWLS estimator subsequently used for the structural model. The measurement model was evaluated by examining fully standardized factor loadings, composite reliability, and average variance extracted (AVE). Because the one-factor model contained three indicators and was just-identified, global fit indices were not informative; consequently, evaluation focused on the standardized loadings, composite reliability, and AVE. The heterotrait-monotrait ratio of correlations (HTMT) could not be calculated because ChatGPT value was the only construct assessed using multiple indicators. Consequently, no pair of latent constructs was available for assessing discriminant validity through HTMT. For the SEM, we examined the following model-fit indices: the comparative fit index (CFI), the Tucker Lewis index (TLI), the root-mean-square error of approximation (RMSEA), and the standardized root mean square residual (SRMR), with CFI and TLI > .950, RMSEA < .080, and SRMR < .060 as thresholds for good model fit (Hu & Bentler, 1999). We considered Keith's (2015) recommendations indicating $|\beta s| \leq .050$ as negligible, $.050 < |\beta s| \leq .100$ as small, $.100 < |\beta s| \leq .250$ as moderate, and $|\beta s| > .250$ as large. Our sample size was appropriate for SEM (Kline, 2016), with a ratio of observations to estimated parameters of 127:1 (11,427 participants for 90 estimated parameters). The final dataset contained no missing data for the variables included in this analysis. Potential multicollinearity among the predictors entered simultaneously in the model equations was examined using variance inflation factors (VIFs) and tolerance values. VIF values below 5 and tolerance values above .20 were considered indicative of an absence of problematic multicollinearity. VIF values ranged from 1.12 to 1.33, and tolerance values ranged from .752 to .894: VIF and tolerance values were 1.23 and .815 for ChatGPT use, 1.12 and .894 for ChatGPT control, and 1.33 and .752 for ChatGPT value. These results indicated low multicollinearity among the predictors. For this auxiliary diagnostic, ChatGPT value was represented by the mean score of its three indicators.

For the second aim, measurement invariance (MI) and multi-group SEM were subsequently used to examine whether the latent construct was measured equivalently and whether the structural relations were comparable across gender, study field, and cultural context (Putnick & Bornstein, 2016; Rosseel, 2012). For the MI, we applied a series of successive constraints to the SEM concerning its form, items' factor loadings, and items' intercepts. We examined changes in model fit (CFI, TLI, RMSEA, and SRMR) after constraining the model configuration (configural invariance), then adding constraints about items' factor loadings (metric invariance), and finally also intercepts (scalar invariance). For the multi-group SEM, we compared an unconstrained or free model (with path coefficients estimated freely in each group) to a constrained model (with path coefficients forced to be equal across groups), calculating changes in CFI, TLI, RMSEA, and SRMR. The overall equality of the structural paths across groups was assessed by comparing the free and constrained models using a chi-square difference test. We then conducted path-specific comparisons of the structural relations across groups. Fully standardized coefficients and their 95% confidence intervals (CIs) were estimated separately for each gender, study field, and cultural context group. The equality of the corresponding standardized regression coefficients was tested using Wald tests (Klopp, 2020). Holm correction was applied across the 23 path-specific comparisons within each grouping variable, and the maximum absolute difference between group-specific standardized coefficients ($\Delta\beta$) was reported as a descriptive measure of structural heterogeneity. For MI testing, changes in model fit were evaluated according to Chen's (2007) recommendations. Invariance was considered supported when ΔCFI was $\leq .010$ and ΔRMSEA was $\leq .015$; ΔSRMR thresholds of $\leq .030$ for metric invariance and $\leq .010$ for scalar invariance were applied. For the multi-group structural comparisons, changes in CFI, TLI, RMSEA, and SRMR were additionally examined as descriptive indices of global fit deterioration, with ΔCFI $\leq .010$ used as an additional indication of structural comparability (Deng et al., 2005). For the analyses across cultural context, we excluded 481 participants for whom the data about HDI were missing (the same happened for the subsequent analysis, i.e., the linear mixed model, LMM).

As regards the third aim, a LMM (lme4 package, Bates et al., 2015; emmeans package, Lenth, 2021; effects package, Fox & Weisberg, 2018; and car R package, Fox & Weisberg, 2019) was selected because each participant provided ratings for seven epistemic emotions, resulting in repeated observations nested within individuals. Consequently, the emotion scores were not statistically independent, and a conventional analysis based on independent observations would have underestimated this within-participant dependence. The mixed-effects approach accounted for the repeated-measures structure by including participant-specific random intercepts, while simultaneously estimating the effects of emotion type and the between-participant factors of gender, study field, and cultural context, together with their interactions. This approach was also suitable for the unequal numbers of participants across groups. Potential multicollinearity among the fixed-effect predictors was assessed using generalized variance inflation factors (GVIFs). Dimension-adjusted GVIF values were 1.000 for emotion type, 1.022 for gender, 1.019 for study field, and 1.014 for cultural context. These values, all close to 1, indicated negligible multicollinearity among the predictors. Satterthwaite's approximation was used to estimate denominator degrees of freedom and produce the Type III analysis of variance table for the fixed effects (lmerTest package, Kuznetsova et al., 2017). Estimated marginal means were used to interpret significant interactions and obtain model-adjusted pairwise comparisons. Bonferroni correction was applied to the post-hoc tests to control the familywise error rate, with significance set at $p < .050$. For the standardized mean differences reported in the SM, we interpreted absolute Cohen's (1988) d values as negligible when $|d| < .20$, small when $.20 \leq |d| < .50$, moderate when $.50 \leq |d| < .80$, and large when $|d| \geq .80$. Finally, an Akaike Information Criterion (AIC)-based model-selection procedure with forward and backward stepwise searches was used to compare candidate models and identify the model with the lowest AIC and the best balance between fit and complexity. The most complex model was the full model (i.e., the model with all main effects and interactions), and the least complex was the null model (i.e., the model with only intercept and random effect); all the other models had a level of complexity between these two models. The full model included participants as a random effect; gender (male and female), study field (arts and humanities, social sciences, applied sciences, and natural and life sciences), and cultural context (low HDI, medium HDI, high HDI, and very high HDI) as between-subject fixed effects; emotion type (surprise, curiosity, enjoyment, confusion, anxiety, frustration, and boredom) as within-subject fixed effect; all the two-way, three-way, and four-way interactions between the fixed effects; and the score of epistemic emotions as dependent variables. As regards cultural context, we included only one indicator for parsimony. Considering the measure about citizenship and the one about the country in which participants were studying, we selected the former because it is less transient.

3.5. Transparency and openness

We report how we recruited participants, how we determined the adequacy of our sample size, all data exclusions, and all measures. The study follows Journal Article Reporting Standards (JARS; Appelbaum et al., 2018). All data have been made publicly available at the Open Science Framework repository and can be accessed at https://osf.io/jcrqy/?view_only=375905c27b3d423b9924cfe398572ce4. Data were analyzed using R; the corresponding packages are reported in the Data Analysis section. This study's design and its analysis were not pre-registered.

4. Results

4.1. Structural equation model

The separate CFA supported the measurement quality of the ChatGPT value construct. Fully standardized factor loadings ranged from .719 to .803, composite reliability was $\omega = .762$, and AVE $= .573$. The AVE exceeded the conventional .50 benchmark, indicating that the latent construct accounted for more than half of the variance in its indicators.

Fig. 2 presents the estimated SEM, whereas Table 1 reports the intercorrelations and descriptive statistics. The complete factor loadings and structural-path estimates are provided in Table D of the SM. The factor loadings for the ChatGPT value were very good, statistically significant at $p < .001$, and ranged from .729 to .780. The SEM had a good fit, $\chi^2(18, N = 11{,}427) = 870.630$, $p < .001$, CFI $= .989$, TLI $= .968$, RMSEA $= .064$, SRMR $= .030$. Most of the structural paths were significant at $p < .001$, except for two paths significant at $p < .010$ (ChatGPT use-curiosity, ChatGPT control-boredom), one path significant at $p < .050$ (ChatGPT control-curiosity), and four nonsignificant paths (ChatGPT use-surprise, ChatGPT use-anxiety, ChatGPT use-boredom, ChatGPT control-confusion). The SEM explained 3% of the variance for ChatGPT control and 25% for ChatGPT value; for epistemic emotions, it explained 13% for surprise, 19% for curiosity, 23% for enjoyment, 1% for confusion, 1% for anxiety, 1% for frustration, and 4% for boredom.

Concerning the relation between ChatGPT use and proximal antecedents of epistemic emotions, we found a positive link both for ChatGPT control ($\beta = .174$, $p < .001$) and ChatGPT value ($\beta = .499$, $p < .001$) – moderate for the former and large for the latter – corroborating Hypothesis 1a. As for the relation between ChatGPT control and epistemic emotions, we found a negligible positive link with curiosity ($\beta = .024$, $p = .033$), small negative links with surprise ($\beta = -.069$, $p < .001$), enjoyment ($\beta = -.058$, $p < .001$), and anxiety ($\beta = -.098$, $p < .001$), and negligible negative links with frustration ($\beta = -.047$, $p < .001$) and boredom ($\beta = -.035$, $p = .002$). Regarding ChatGPT value, there were large positive links with positive emotions (surprise: $\beta = .382$, $p < .001$; curiosity: $\beta = .443$, $p < .001$; enjoyment: $\beta = .476$, $p < .001$); a negligible positive link with anxiety ($\beta = .043$, $p < .001$), a negligible negative link with confusion ($\beta = -.050$, $p < .001$), a small

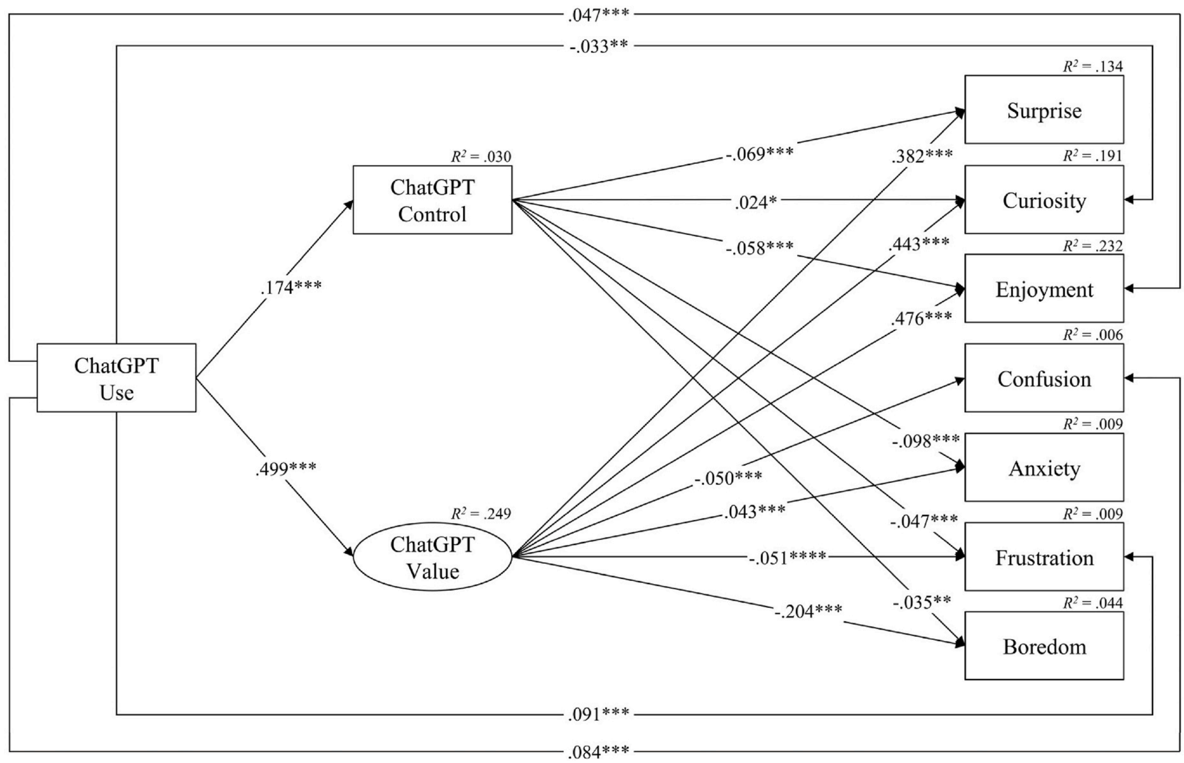

Fig. 2. Structural equation model (SEM) of the relations between ChatGPT use, proximal antecedents (ChatGPT control and ChatGPT value), and epistemic emotions (surprise, curiosity, enjoyment, confusion, anxiety, frustration, and boredom). For parsimony, only significant paths are presented. *p < .050. **p < .010. ***p < .001.

Table 1
Intercorrelations, means (*Ms*), standard deviations (*SDs*), and 95% confidence intervals (CIs) for ChatGPT use, ChatGPT control, ChatGPT value, and epistemic emotions (surprise, curiosity, enjoyment, confusion, anxiety, frustration, and boredom) included in the structural equation model (SEM).

Variable	1	2	3	4	5	6	7	8	9	10
1. ChatGPT use	-									
2. ChatGPT control	.174***	-								
3. ChatGPT value	.428***	.324***	-							
4. Surprise	.179***	.073***	.292***	-						
5. Curiosity	.181***	.177***	.338***	.441***	-					
6. Enjoyment	.262***	.123***	.389***	.530***	.487***	-				
7. Confusion	.054***	−.015	−.006	.234***	.181***	.155***	-			
8. Anxiety	.019*	−.067***	.020*	.257***	.097***	.197***	.380***	-		
9. Frustration	.053***	−.047***	−.016	.171***	.090***	.107***	.543***	.455***	-	
10. Boredom	.082***	−.102***	−.164***	.062***	−.005	−.017	.314***	.308***	.371***	-
M	2.482	3.554	3.581	2.849	3.447	2.913	2.539	2.044	2.192	2.255
SD	1.088	.994	.792	1.191	1.162	1.270	1.096	1.110	1.104	1.035
95% CI	[2.462, 2.502]	[3.536, 3.572]	[3.566, 3.595]	[2.827, 2.871]	[3.425, 3.468]	[2.889, 2.936]	[2.518, 2.558]	[2.024, 2.064]	[2.171, 2.212]	[2.236, 2.274]

*p < .05. **p < .01. ***p < .001.

negative link with frustration (β = −.051, p < .001), and a moderate negative link with boredom (β = −.204, p < .001). These results partially supported Hypothesis 1b.

Moreover, ChatGPT use showed statistically significant but negligible associations with curiosity (β = −.033, p = .003) and enjoyment (β = .047, p < .001), and small positive associations with confusion (β = .084, p < .001) and frustration (β = .091, p < .001). Considering the role of ChatGPT control as a mediator, we found that it mediated the relation of ChatGPT use with curiosity (indirect effect: .004, p = .034), enjoyment (−.010, p < .001), and frustration (−.008, p < .001) partially, and with surprise (−.012, p < .001), anxiety (−.017, p < .001), and boredom (−.006, p = .002) totally. Finally, ChatGPT value mediated the relation of ChatGPT use with curiosity (indirect effect: .221, p < .001), enjoyment (.237, p < .001), confusion (−.025, p < .001), and frustration (−.025, p < .001) partially, and with surprise (.190, p < .001), anxiety (.022, p < .001), and boredom (−.102, p < .001) totally. Overall, the emotions that had the strongest mediation effect were surprise, curiosity, and enjoyment, through ChatGPT value. These findings partially confirmed Hypothesis 1c.

Overall, the findings provided partial support for the hypothesized pattern, mainly based on the generalized CVT (Pekrun, 2024): ChatGPT use was positively associated with control and value, and value showed the clearest associations with positive epistemic emotions, whereas the associations involving control were weaker and did not always follow the hypothesized direction.

4.2. Measurement invariance and multi-group SEM

Regarding MI, we took into account CFI changes, and we found that the SEM was characterized by configural, metric, and scalar invariance for gender ($\Delta CFI_{metric\text{-}configural} = -.001$; $\Delta CFI_{scalar\text{-}metric} = .000$), study field ($\Delta CFI_{metric\text{-}configural} = .000$; $\Delta CFI_{scalar\text{-}metric} = .001$), and cultural context ($\Delta CFI_{metric\text{-}configural} = .001$; $\Delta CFI_{scalar\text{-}metric} = -.003$). The same was confirmed by examining changes in TLI, RMSEA, and SRMR (Table 2). These results indicated that the latent construct was measured equivalently across groups. We then conducted the multi-group SEM. Chi-square difference tests comparing the free and constrained models indicated significant differences for gender, $\chi^2(23) = 55.661$, $p < .001$, study field, $\chi^2(69) = 169.640$, $p < .001$, and cultural context, $\chi^2(69) = 264.596$, $p < .001$. Given the large sample size, we also considered changes in global fit indices. Changes in CFI were small across gender ($\Delta CFI = -.000$), study field ($\Delta CFI = -.002$), and cultural context ($\Delta CFI = -.004$), with similarly limited changes in TLI, RMSEA, and SRMR (Table 3). Thus, although the chi-square difference tests indicated statistically significant global differences across all grouping variables, the small changes in global fit indices suggested that these differences were limited in magnitude. We therefore examined the pattern in greater detail through path-specific comparisons of the structural coefficients across gender, study field, and cultural context groups. Complete gender-specific, study field-specific, and cultural context-specific coefficients, CIs, coefficient differences, and Wald tests are reported in Tables E, F, and G of the SM, respectively.

Across gender groups, 22 of the 23 structural paths did not differ significantly after correction for multiple testing. Only the association between ChatGPT value and enjoyment showed significant between-group heterogeneity, Wald $\chi^2(1) = 10.736$, Holm-adjusted $p = .024$, maximum $\Delta\beta = .089$. The association was positive in both groups but stronger in the female group, $\beta = .514$, 95% CI [.484, .543], than in the male group, $\beta = .425$, 95% CI [.389, .461]. All remaining path-specific comparisons were nonsignificant after Holm correction, with adjusted p-values ranging from .757 to 1.000. The corresponding differences in standardized coefficients were small, with maximum $\Delta\beta$ values no greater than .048. Thus, the results indicated substantial structural stability across gender groups, with only a modest gender-related difference in the value-enjoyment association.

Across study field groups, 22 of the 23 structural paths did not differ significantly after correction for multiple testing. Only the association between ChatGPT value and surprise showed significant between-group heterogeneity, Wald $\chi^2(3) = 15.163$, Holm-adjusted $p = .039$, maximum $\Delta\beta = .178$. The association was positive in all four groups but strongest in the social sciences group, $\beta = .459$, 95% CI [.392, .526], and weakest in the natural and life sciences group, $\beta = .281$, 95% CI [.204, .358]. All remaining path-specific comparisons were nonsignificant after Holm correction, with adjusted p-values ranging from .118 to 1.000. The corresponding differences in standardized coefficients were generally limited, with maximum $\Delta\beta$ values no greater than .135. Thus, the results indicated substantial structural stability across study field groups, with only one localized difference in the strength of the value-surprise association.

Across cultural context groups, 19 of the 23 structural paths did not differ significantly after correction for multiple testing. Four paths showed significant between-group heterogeneity: ChatGPT use with value, Wald $\chi^2(3) = 22.310$, Holm-adjusted $p = .001$, maximum $\Delta\beta = .133$; ChatGPT control with curiosity, Wald $\chi^2(3) = 18.155$, Holm-adjusted $p = .009$, maximum $\Delta\beta = .155$; ChatGPT control with enjoyment, Wald $\chi^2(3) = 14.739$, Holm-adjusted $p = .041$, maximum $\Delta\beta = .156$; and ChatGPT value with curiosity, Wald $\chi^2(3) = 36.032$, Holm-adjusted $p < .001$, maximum $\Delta\beta = .264$. The use-value and value-curiosity associations remained positive across all HDI groups but varied in strength. By contrast, the control-curiosity and control-enjoyment coefficients were comparatively small and varied around zero across groups, indicating more limited and context-dependent heterogeneity. Thus, most structural relations were stable across cultural context groups, although the strength of a small number of paths differed. To sum up, these results corroborated Hypothesis 2.

4.3. Linear mixed models

Consistent with the exploratory nature of Aim 3, we examined differences in epistemic emotions across gender, study field, and cultural context without testing directional hypotheses. Before considering the inferential tests, the overall pattern of the estimated marginal means indicated that curiosity had the highest score, followed by enjoyment, surprise, confusion, boredom, frustration, and anxiety. Thus, the three positive epistemic emotions generally showed higher scores than the four negative emotions, although surprise and confusion were relatively close compared with the other positive-negative emotion contrasts.

Using the AIC model selection procedure, we identified the best model (see Table H of the SM), which included the effects of gender, study field, cultural context, and emotion type, six two-way interactions (i.e., gender × field, gender × context, field × context, gender × emotion, field × emotion, context × emotion), and three three-way interactions (i.e., gender × field × emotion, gender × context × emotion, field × context × emotion). In the SM, we reported in Table I the post-hoc tests about the significant main factors and three-way interactions.

The LMM revealed a significant effect of gender, $F(1, 10{,}946) = 5.647$, $p = .017$: males ($M = 2.623$, $SD = 1.242$, 95% CI [2.609, 2.635]) had higher scores than females ($M = 2.579$, $SD = 1.221$, 95% CI [2.573, 2.585]); however, the magnitude of this difference was negligible. Also cultural context, $F(3, 10{,}946) = 8.121$, $p < .001$, had a significant effect, with scores higher for students from low HDI countries ($M = 2.737$, $SD = 1.239$, 95% CI [2.696, 2.778]) – which did not differ from scores from medium HDI countries ($M = 2.670$, $SD = 1.212$, 95% CI [2.637, 2.702]) – compared to those from high ($M = 2.602$,

Table 2
Measurement invariance results at the configural, metric, and scalar levels across gender (male and female), study field (arts and humanities, social sciences, applied sciences, and natural and life sciences), and cultural context (based on the citizenship human development index – HDI).

Groups	Model	χ^2	df	p	CFI	TLI	RMSEA	SRMR	ΔCFI	ΔTLI	ΔRMSEA	ΔSRMR
Gender	Configural invariance	966.930	59	< .001	.989	.979	.052	.031	–	–	–	–
	Metric invariance	996.992	61	< .001	.988	.979	.052	.031	−.001	.000	.000	.000
	Scalar invariance	1069.645	91	< .001	.988	.985	.044	.031	.000	.006	−.008	.000
Study Field	Configural invariance	1082.203	141	< .001	.988	.982	.048	.032	–	–	–	–
	Metric invariance	1107.213	147	< .001	.988	.982	.048	.033	.000	.000	.000	.001
	Scalar invariance	1149.218	237	< .001	.989	.990	.038	.032	.001	.008	.010	.000
Citizenship HDI	Configural invariance	1167.344	141	< .001	.987	.980	.052	.034	–	–	–	–
	Metric invariance	1147.922	147	< .001	.988	.982	.050	.034	.001	.002	−.002	.000
	Scalar invariance	1420.952	237	< .001	.985	.987	.043	.033	−.003	.005	−.007	−.001

Note. df = degrees of freedom; TLI = Tucker Lewis index; RMSEA = root-mean-square error of approximation; SRMR = standardized root mean square residual; CFI = comparative fit index; Δ = change.

Table 3
Multi-group structural equation model (SEM) results across gender (male and female), study field (arts and humanities, social sciences, applied sciences, and natural and life sciences), and cultural context (based on the citizenship human development index – HDI).

Groups	Model	χ^2	df	p	CFI	TLI	RMSEA	SRMR	ΔCFI	ΔTLI	ΔRMSEA	ΔSRMR
Gender	Free model	913.476	36	< .001	.989	.967	.065	.030	–	–	–	–
	Constrained model	981.025	59	< .001	.989	.979	.052	.031	.000	.012	−.013	.001
Study Field	Free model	922.018	72	< .001	.990	.968	.064	.030	–	–	–	–
	Constrained model	1091.655	141	< .001	.988	.982	.049	.033	−.002	.014	−.015	.003
Citizenship HDI	Free model	832.118	72	< .001	.991	.972	.062	.029	–	–	–	–
	Constrained model	1169.689	141	< .001	.987	.980	.052	.034	−.004	.008	−.010	.005

Note. df = degrees of freedom; TLI = Tucker Lewis index; RMSEA = root-mean-square error of approximation; SRMR = standardized root mean square residual; CFI = comparative fit index; Δ = change. The free model is the model in which structural path coefficients are estimated freely across groups. The constrained model is the model in which structural path coefficients are constrained to be equal across groups.

SD = 1.236, 95% CI [2.589, 2.616]) and very high HDI countries (M = 2.578, SD = 1.225, 95% CI [2.565, 2.591]), although the effect sizes for these differences were negligible. Moreover, emotion type had a significant effect, $F(6, 65{,}676) = 708.560$, $p < .001$ (Fig. 3). Post-hoc tests indicated that: curiosity (M = 3.452, SD = 1.161, 95% CI [3.431, 3.474]) was higher than enjoyment (M = 2.909, SD = 1.272, 95% CI [2.885, 2.933]), with a moderate effect size; enjoyment was higher than surprise (M = 2.847, SD = 1.192, 95% CI [2.825, 2.870]), although the difference was negligible; surprise was higher than confusion (M = 2.534, SD = 1.096, 95% CI [2.513, 2.554]), with a small effect size; confusion was higher than boredom (M = 2.249, SD = 1.032, 95% CI [2.229, 2.268]), although the difference was negligible; boredom in turn was higher than frustration (M = 2.186, SD = 1.102, 95% CI [2.165, 2.207]) – not differing from anxiety (M = 2.037, SD = 1.108, 95% CI [2.016, 2.058]) – with negligible effect sizes.

These main effects were moderated by four significant two-way interactions: field × context, $F(9, 10{,}946) = 2.752$, $p = .003$, gender × emotion, $F(6, 65{,}676) = 3.226$, $p = .004$, field × emotion, $F(18, 65{,}676) = 5.600$, $p < .001$, and context × emotion, $F(18, 65{,}676) = 25.070$, $p < .001$. In turn, they were moderated by the three significant three-way interactions. Examining the post-hoc tests, we found that males had higher scores than females only for surprise, and the magnitude of this difference was negligible: Considering the gender × field × emotion interaction, $F(18, 65{,}676) = 2.223$, $p = .002$ (Figure A of the SM), such difference regarded only social sciences students; for the gender × context × emotion interaction, $F(18, 65{,}676) = 2.825$, $p < .001$ (Figure B of the SM), only high HDI countries. In all the other cases, males' and females' scores did not differ. Concerning the field × context × emotion interaction, $F(54, 65{,}676) = 2.992$, $p < .001$ (Figure C of the SM), the post-hoc tests revealed significant differences for four emotions. Among arts and humanities students, surprise was greater in low HDI vs. high and very high HDI countries, with moderate effect sizes. With effect sizes ranging from small to moderate, enjoyment was higher for social sciences students, for low vs. high and very high HDI countries, and for medium vs. very high HDI countries; for applied sciences students, for low and medium vs. high and very high HDI countries; and for natural and life sciences students, for medium vs. high and very high HDI countries. Confusion was lower, for applied sciences students, for low and medium vs. high HDI countries, with small effect sizes. Finally, with effect sizes ranging from small to large, anxiety was higher, for arts and humanities students, for low vs. high and very high HDI countries; for social sciences students, for medium vs. high and very high HDI countries; for applied sciences students, for low vs. high and very high HDI countries, for medium vs. very high HDI countries, and for high vs. very high HDI countries; and for natural and life sciences, for medium vs. very high HDI countries. To sum up, in the case of significant HDI differences for students of some study fields, enjoyment, surprise, and anxiety diminished as HDI rose, while confusion increased.

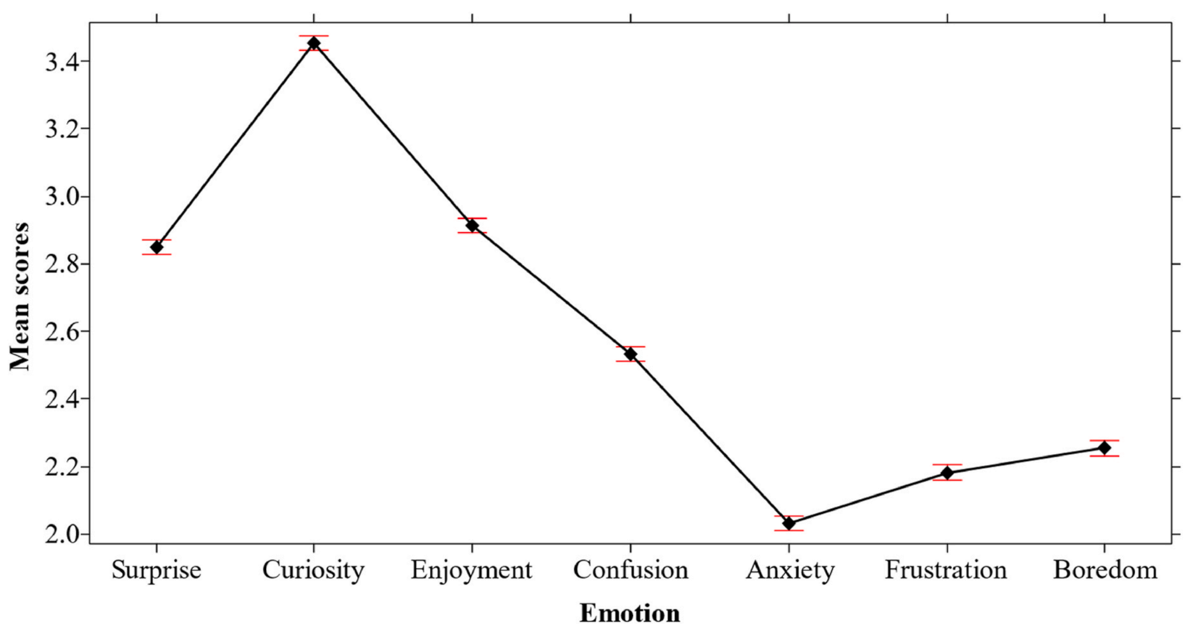

Fig. 3. Mean levels of epistemic emotions (surprise, curiosity, enjoyment, confusion, anxiety, frustration, and boredom). The bars represent the 95% confidence intervals (CIs).

5. Discussion

Developing knowledge while dealing with generative AI is a normative everyday task for tackling the challenges of our 21st-century digital society (Guo et al., 2022), also for HE students (Abdaljaleel et al., 2024; Ravšelj et al., 2025). Using ChatGPT – the most widely disseminated interactive generative AI system (OpenAI, 2025; Wu et al., 2023) – encompasses the typical characteristics of tasks that arouse epistemic emotions. The latter can be conceptualized as those emotions whose object focus is knowledge building (Muis et al., 2018; Pekrun et al., 2017; Pekrun & Loderer, 2020). In the peculiar case of an individual interacting with ChatGPT, knowledge building can refer to at least two elements: on the one hand, the process through which the individual and AI co-jointly develop knowledge; on the other hand, the product deriving from the interaction between the individual and AI. Through our findings, we contributed to extending knowledge about the nature of these emotions in a large and internationally diverse sample of HE students, while providing qualified support for the cross-group stability of the relations proposed by Pekrun's generalized CVT (2024), with a specific focus on ChatGPT use, control, and value as antecedents.

5.1. Epistemic emotions and their antecedents across gender, study field, and cultural context

5.1.1. Relations between ChatGPT use and proximal antecedents of epistemic emotions

As regards the relation between ChatGPT use and proximal antecedents of epistemic emotions (Aim 1), the SEM revealed that HE students who declared to use ChatGPT more frequently in turn perceived themselves to control and value it more, in terms of interest, importance, and utility (Goetz et al., 2010; Muis, Psaradellis, et al., 2015; Putwain et al., 2018), supporting Hypothesis 1a. The occurrence of a moderate relation for control vs. a large one for value was in line with previous literature involving HE students, describing contradictory results for control (Bouteraa et al., 2024; Grassini et al., 2024; Oubibi et al., 2025; Strzelecki, 2023; Tiwari et al., 2024; Wu et al., 2024) and more consistent findings for value (Ofosu-Ampong et al., 2023; Tiwari et al., 2024; Yilmaz et al., 2023). On the one hand, different reasons can be at the basis of the heterogeneous array of results documented for ChatGPT control, such as the presence of varying amounts of control in different HE student samples, polarized at low or high levels (Abdaljaleel et al., 2024; Strzelecki, 2023; Tiwari et al., 2024); the investigation of the impact of control on use or intention/acceptance to use ChatGPT through cross-sectional designs (Grassini et al., 2024; Strzelecki, 2023; Tiwari et al., 2024); or the existence of different conceptualizations of control, in terms for example of ease of use (Grassini et al., 2024; Strzelecki, 2023; Tiwari et al., 2024) or self-efficacy (Bouteraa et al., 2024; Oubibi et al., 2025; Wu et al., 2024). However, the identified positive and moderately significant relation is in line with research measuring HE students' self-efficacy using experimental designs (Oubibi et al., 2025; Wu et al., 2024). Coherently with suggestions based on TAM (Davis, 1989; Granić & Marangunić, 2019; Venkatesh et al., 2012), our result documents that, at least after its early release, using ChatGPT was strictly interconnected with the perception of being able to use it, a fundamental prerequisite of success in learning (Pekrun, 2024). Future research should examine whether this depends on the stage of ChatGPT or, rather, on the chatbot's effective intuitive usability. On the other hand, regarding value, our findings indicated that more frequent ChatGPT use was strongly associated with greater perceived value, consistent with the variety of functions for which students report appreciating ChatGPT (Ravšelj et al., 2025). In any case, we extended previous research, which focused mainly on the impact of value on ChatGPT use and not vice versa. Alternative explanations should also be considered. Because the data were cross-sectional, the observed associations may reflect greater familiarity accompanying more frequent ChatGPT use, but students who already perceived ChatGPT as manageable, interesting, or useful may also have been more inclined to use it frequently. In addition, unmeasured factors such as prior digital competence, access to generative AI, academic demands, or previous successful experiences with ChatGPT may have been associated with both usage frequency and students' appraisals. Longitudinal and experimental research is therefore needed to clarify the direction and mechanisms of these associations.

Overall, the associations between ChatGPT use and its proximal antecedents were substantively meaningful, with a moderate relation for control and a large relation for value. Thus, the clearest pattern concerned the link between more frequent ChatGPT use and stronger perceptions of its interest, importance, and utility.

5.1.2. Relations between proximal antecedents and epistemic emotions

Considering the links between ChatGPT control and value, on the one hand, and epistemic emotions, on the other hand, our data help shape a more complex framework and address gaps in knowledge regarding the role of these antecedents for HE students about ChatGPT use. All the aforementioned relations were significant except the one between control and confusion. The most notable pattern regards the strong association between value and positive emotions: the more HE students perceived ChatGPT as interesting, important, and useful, the more frequently they felt surprised, curious, and excited while using it, corroborating Hypothesis 1b. These same relations have already been documented with students from primary school to HE institutions about STEM for curiosity and enjoyment (Muis, Psaradellis, et al., 2015; Munzar et al., 2021; Pekrun et al., 2017; Schubert et al., 2023).

While surprise is typically linked to incongruity (Pekrun, 2024; Reisenzein et al., 2019), the present findings suggest that perceived value may also be relevant to students' experience of surprise during ChatGPT use. One tentative interpretation is that unexpected outputs may be experienced more positively when students already regard ChatGPT-supported activities as interesting, important, or useful. More generally, students who perceive ChatGPT-supported activities as interesting, important, or useful may engage more actively with the generated information. Greater value may encourage them to formulate further questions, compare ChatGPT outputs with their prior knowledge or expectations, and explore discrepancies or novel information. These processes may foster curiosity and surprise, while the perceived relevance and usefulness of the activity may also make the interaction more enjoyable. However, these mechanisms were not directly assessed and should therefore be examined in future process-oriented or experimental studies.

As for control, there was a positive but almost negligible link with curiosity: the more HE students felt that the situation was under their control when using ChatGPT, the more they were curious about ChatGPT knowledge-building processes and/or corresponding products. In other words, curiosity would necessitate the confidence that possible knowledge gaps can be filled (Pekrun, 2024). These findings again support Hypothesis 1b, extending the literature about HE students' mathematics (Schubert et al., 2023). Unexpectedly, there were small negative links between control and the other positive emotions, with higher frequencies of surprise and enjoyment (operationalized here as excitement) at lower levels of control and vice versa. It is also worth noting that positive associations between control and enjoyment assumed by previous literature were sometimes based on a conceptualization of the latter in terms of delight, and that findings about surprise are somewhat inconsistent due to its diverse conceptualization as a positive, neutral, or negative emotion, and its opposite cascading effects (Chevrier et al., 2019; Pekrun, 2024; Vogl et al., 2019). Nevertheless, the negative links between control on the one hand and surprise and excitement on the other hand may tentatively be interpreted by considering other typical antecedents of epistemic emotions (D'Mello et al., 2014; Muis, Pekrun, et al., 2015), such as novelty and cognitive conflict or discrepancy between previous knowledge or expectations and knowledge developed by ChatGPT. If ChatGPT outputs are perceived as adequate or particularly useful, such discrepancies might be experienced as pleasant and could be associated with surprise or excitement, even when students perceive limited control over the interaction. Future research should examine how factors such as control, value, novelty, and discrepancy jointly relate to the generation of epistemic emotions.

Also for negative emotions, Hypothesis 1b was almost confirmed. For control, there were negative associations, small for anxiety and very small for frustration and boredom – but not significant for confusion. This is consistent with previous literature on STEM among primary school to HE students (Dowd et al., 2015; Muis, Psaradellis, et al., 2015; Munzar et al., 2021; Schubert et al., 2023), specifically for anxiety and boredom. Our results could be interpreted by considering the peculiar characteristics of interacting with ChatGPT, together with taking into account the epistemic nature of these emotions. On these bases, we could expect, for example, that anxiety can emerge when an individual is afraid of a possible future failure when dealing with a problem with the help of ChatGPT; that frustration can originate when the solution offered by ChatGPT is not considered adequate or satisfying; and that boredom can be triggered by the lack of engagement with the ongoing knowledge-building processes. And it is reasonable to presume that these and similar situations frequently occur when the perceived capability to perform well in a task, such as using ChatGPT, is low. In addition, we could speculate that in this specific context, confusion should be triggered by puzzling and difficult-to-understand or inappropriate solutions offered by the chatbot, which however could probably not depend on students' abilities to interact with it – in light of ChatGPT's very sophisticated abilities to manage complex interactions with users by interpreting and responding in a manner approximating human behavior (Wu et al., 2023) – but, rather, to other limitations of the instruments, such as its difficulties to take into account a user's context (Cress & Kimmerle, 2023).

Also, value was negatively associated with negative emotions, consistent with previous studies (Muis, Psaradellis, et al., 2015; Munzar et al., 2021; Pekrun et al., 2017; Schubert et al., 2023) – but there was the exception of the very small positive link with anxiety. On the one hand, the SEM revealed that the higher the value attributed to ChatGPT, the less frequent confusion, frustration, and boredom. In other words, a high value would protect against the risk of being overwhelmed by the cognitive gap associated with confusion, of being caught by the mixture of sadness and anger typical of frustration, and of disengaging from the knowledge-building processes and products relating to ChatGPT. Future studies should examine if this protective factor characterizes only the first users of ChatGPT, similar to hedonic motivation and fun, which are particularly salient in the early periods in which a new technology is available (Grassini et al., 2024). For anxiety, we found the usual pattern characterizing achievement emotions, with increases of such emotions for students with low control and a high value, also in some technological tasks (Pekrun, 2024; Pekrun & Loderer, 2020).

Overall, however, the magnitude of the observed associations varied considerably. Given the very large sample size, statistical significance did not always indicate substantive importance. In particular, the associations of ChatGPT control with curiosity, frustration, and boredom, as well as those of ChatGPT value with anxiety and confusion, were negligible and should therefore be interpreted cautiously. By contrast, the clearest pattern concerned the large associations between ChatGPT value and the positive epistemic emotions.

5.1.3. Mediation of ChatGPT control and value in the relations between ChatGPT use and epistemic emotions

Concerning the possible mediating role of the proximal antecedents in the relations between ChatGPT use and epistemic emotions, our aim was exploratory. Previous research focused sparsely on some of the relations that we were interested in, with inconsistent associations between HE students' emotions, such as enjoyment and anxiety on the one hand and ChatGPT use or intention to use it on the other hand (Grassini et al., 2024; Lo et al., 2024; Strzelecki, 2023; Tiwari et al., 2024). Supporting Hypothesis 1c, we found that the associations between ChatGPT use and HE students' epistemic emotions were generally characterized by indirect associations through control and value, with the strongest indirect associations involving value and positive emotions such as surprise, curiosity, and enjoyment. For surprise, the direct association with ChatGPT use was nonsignificant once control and value were included in the model, whereas the indirect associations through these appraisals remained significant.

Viewed through the generalized CVT (Pekrun, 2006, 2024), the findings support the proposed role of control and value as proximal appraisals associated with students' epistemic emotions during ChatGPT use. In particular, value showed the clearest and strongest associations with positive emotions, consistent with the proposition that emotions depend partly on the subjective importance, interest, and utility attributed to an activity. The negative associations of control and value with several negative emotions were also broadly consistent with the theory. However, the weaker and occasionally unexpected associations involving control indicate that the relative contribution of the two appraisals may depend on the specific emotion and characteristics of ChatGPT-supported knowledge activities. Thus, the findings provide partial rather than uniform support for the generalized CVT in this context.

5.1.4. Invariance across gender, study field, and cultural context

Through the measurement-invariance analyses and multi-group SEM, we examined whether the measurement properties of ChatGPT value and the structural relations among the study variables were comparable across gender, study field, and cultural context groups (Aim 2). The results indicated that factor loadings and intercepts were stable across groups and that, despite significant global differences in the structural models, the path-specific analyses showed broad comparability of most structural relations, providing qualified support for Hypothesis 2. Overall, the path-specific analyses indicated substantial, although not complete, structural stability across gender, study field, and cultural context groups. Most of the 23 structural paths were comparable across groups, with only one differing path for gender, one for study field, and four for cultural context, after correction for multiple testing. These localized differences do not overturn the broader evidence of cross-group stability, which provides qualified support for the relations proposed by the generalized CVT (Pekrun, 2006, 2024) in the context of ChatGPT use. However, they should not be interpreted as demonstrating universal relations or as establishing generalizability to all HE students, countries, or educational contexts, given the convenience sampling strategy, possible self-selection and non-response biases, and unequal representation across countries.

5.1.5. Differences in epistemic emotions according to gender, study field, and cultural context

Examining the mean values of the seven epistemic emotions (Aim 3), our analyses revealed a higher frequency of positive emotions (in decreasing order: curiosity, enjoyment, and surprise) over negative ones (confusion, boredom, frustration, and anxiety) for HE students' use of ChatGPT. This is coherent with findings about sentiment-analysis data on the prevalence of positive ChatGPT-related emotions for the general population and referred to HE (Demirel et al., 2025; Lo et al., 2024; Mamo et al., 2024), and also with the presence of mixed positive and negative emotions in HE students (Lo et al., 2024). They also support assumptions of the CVT (Pekrun, 2006, 2024) about varying emotion rates according to individual and contextual factors, extending them to the specific task of using ChatGPT for HE students from more than 127 countries. Future research should examine whether these reactions are related to the initial release of ChatGPT and remain stable even as novelty transforms into habit (Grassini et al., 2024).

Our data revealed only some sparse gender differences, mainly about surprise, in some cases more frequent for males. Unexpectedly, they did not regard anxiety, usually prevalent among HE female vs. male students

(Tan et al., 2023). We speculate that certain characteristics of the interaction with ChatGPT may account for the lack of such differences. For example, interacting privately with a chatbot, without people around and without salient stereotypical expectations about males' better performance, could be a factor responsible for a possible diminishment in social pressure and associated anxiety. Moreover, ChatGPT's adapting mechanisms, resembling human interactions, personalizing the contents and the style used in a conversation (Wu et al., 2023), could be particularly welcome by females, who typically outperform males in theories of mind tasks in which they adapt easily to the mental states of the addressee (Greenberg et al., 2023; Wacker et al., 2017).

Finally, when cultural differences emerged, there was a pattern revealing, for students of some study fields, higher enjoyment, surprise, and anxiety, and lower confusion with worse HDI conditions. This is in line with sentiment-analysis data (Demirel et al., 2025). Students' relevance of knowledge-building processes and products, together with the frequency of emotions usually associated with better learning and epistemic processes (as is the case for enjoyment, surprise, and anxiety vs. confusion; Pekrun, 2024; Schubert et al., 2023), may be higher in countries in which development indexes are lower due, presumably, to the fact that what is at stake in using new technologies weights more in terms of personal opportunities. Future research should explore this speculation further.

However, given the very large sample size, statistical significance did not always correspond to substantive importance. In particular, the significant main effects of gender and cultural context were negligible in magnitude, as were some differences involving emotion type and the interaction effects. Therefore, the overall gender- and HDI-related differences should not be interpreted as substantively meaningful disparities and do not, in isolation, warrant specific educational or policy recommendations.

5.2. Limitations and directions for future research

Our work is characterized by some limitations. First, our convenience sample was not representative of the countries involved and excluded or underrepresented HE students who had difficulty accessing the internet or using electronic devices. Moreover, the survey was available in a limited number of languages, potentially restricting participation to students familiar with them. However, the inclusion of English and Spanish, which are among the most widely spoken languages worldwide, could have partially compensated for this limitation. In addition, participation was voluntary, and students self-selected into the online survey. Therefore, students with greater interest in ChatGPT or generative AI, more frequent access to digital technologies, or greater willingness to report their experiences may have been more likely to participate. Because systematic information on the number and characteristics of eligible students who received the invitation but did not participate was unavailable, response rates and potential non-response bias could not be assessed. These sampling and self-selection issues limit the generalizability of the findings despite the large and internationally diverse sample. Future research should, where feasible, use probability-based or stratified sampling, document recruitment denominators and response rates, and compare respondents and non-respondents using available demographic or institutional information. Moreover, although the sample included participants from 127 countries, the study was designed to examine individual students' experiences rather than to compare national contexts. Therefore, differences in generative AI adoption, educational technology integration, and HE policies across countries were not explicitly examined and may have influenced students' experiences with ChatGPT. In addition, individual-level socioeconomic indicators were not collected; therefore, the HDI-related associations may partly reflect unmeasured differences in students' personal socioeconomic circumstances and should not be interpreted as individual-level effects of national development. Future research should combine individual-level data with country-level indicators, such as AI readiness, institutional AI policies, or national digital education strategies, to better explain cross-national variation. Second, we used self-report measures, which may be biased by social desirability, recall errors, and individual differences in interpreting the response scales. In particular, self-reported ChatGPT use may not accurately reflect actual usage behavior, as participants may have overestimated or underestimated the frequency of their interactions with the chatbot. Nevertheless, self-report measures are still among the richest ways to access mental states (Pekrun & Bühner, 2014). Future research should combine self-reported data with objective behavioral indicators (e.g., usage logs or frequency and duration of interactions) to triangulate findings. Third, we operationalized ChatGPT use, ChatGPT control, and individual epistemic emotions using single-item measures. Although this choice helped reduce respondent burden, cognitive fatigue, and missing data in a large-scale, multilingual survey spanning several domains, these measures do not permit assessment of internal consistency or factorial structure and may provide a less comprehensive representation of the constructs than multi-item scales. In particular, the single items assessing ChatGPT use and control may not have fully captured the complexity of participants' actual usage behavior and control beliefs. Nevertheless, previous research has supported the use of single-item measures (D'Mello & Graesser, 2012; Jarrell et al., 2016; Tong et al., 2005). Future studies should replicate our findings using validated, psychometrically more robust multi-item measures. Fourth, we addressed the main effects of control and value without studying their interaction, which could be relevant in explaining their effects on epistemic emotions (Pekrun, 2024): Future research should address this issue, considering their interactions also with other antecedents of epistemic emotions (e.g., incongruity, novelty, and complexity). Fifth, the emotion items referred to participants' experiences while using ChatGPT, but did not directly assess the object focus, immediate trigger, or specific purpose of each emotional episode. Consequently, although the emotions were theoretically interpreted in relation to ChatGPT-supported knowledge activities, some responses may also have reflected more general reactions to technology use. Future research should explicitly distinguish between epistemic emotions and technology-use emotions by assessing the purpose of the interaction and the object to which each emotion is directed. Sixth, the seven epistemic emotions we measured with the ERES scale (Pekrun et al., 2017) covered only three of the four quadrants of the representation derived from the intersection of the valence and arousal, neglecting positive deactivating emotions. Future studies on interactions with AI should also explore the role of these kinds of epistemic emotions. Seventh, we used a cross-sectional design, so our findings are correlational: Future research should include longitudinal assessments to further examine reciprocal links. Finally, because ChatGPT and related generative AI systems are evolving rapidly, the findings may be specific to the technological features, patterns of use, and institutional context prevailing at the time of data collection. Their temporal generalizability should therefore be interpreted with caution, and future studies should replicate the analyses as generative AI systems and educational practices continue to develop.

5.3. Potential implications for educational practice

From an applied perspective, our findings support the relevance of initiatives aimed at increasing people's awareness of the differences between interacting with ChatGPT and other entities. The interaction with ChatGPT exhibits some typical characteristics of the ZPD and scaffolds as a means of supporting students' knowledge-building by, for example, favoring the development of personal opinions (Ghazal et al., 2020). However, it is important to recognize both similarities and differences between interacting with ChatGPT compared to other face-to-face interactions or online collaborative environments (Cress & Kimmerle, 2023; Ghazal et al., 2020). As described previously, similarities include the higher expertise of one of the (at least) two entities involved in the interaction (Farrokhnia et al., 2024; Ravšelj et al., 2025), the collaborative nature of built knowledge (Cress & Kimmerle, 2023), and the possibility of acquiring the knowledge-transforming writing practices of the expert (Scardamalia & Bereiter, 1987). Nevertheless, it is highly relevant to be aware of some differences in the specific characteristics of using ChatGPT, which can be responsible for peculiar affective reactions that, on some occasions, may reveal themselves as risk factors for students' learning. Such negative reactions can arise, for example, in the case that the resource is temporarily unavailable, when it gives responses not taking into account the students' context (Cress & Kimmerle, 2023), or when it provokes over-dependence (Farrokhnia et al., 2024), undermining self-determination and autonomy of learning processes (Ryan & Deci, 2020). One way to overcome these obstacles is to foster both students' and teachers' awareness about the specific characteristics of their conversational AI partner (Cress & Kimmerle, 2023).

Moreover, knowledge about the nature of HE students' epistemic emotions and their associations with ChatGPT use, control, and value may help generate hypotheses for future educational interventions. For example, previous research suggests that regulating early confusion may reduce the likelihood of subsequent frustration or boredom when difficulties remain unresolved (D'Mello & Graesser, 2012). Similarly, interventions designed to support students' perceived control and task value could be developed and evaluated in longitudinal or experimental studies. However, the present cross-sectional and correlational findings do not demonstrate that modifying control or value will cause changes in epistemic emotions and therefore do not justify specific intervention guidelines or prescriptive policy recommendations.

6. Conclusions

This study provides large-scale, internationally diverse evidence on how ChatGPT use, perceived control, and perceived value are associated with HE students' epistemic emotions. The findings extend the application of the generalized CVT (Pekrun, 2006, 2024) to ChatGPT-supported knowledge activities, showing that value was particularly strongly associated with positive emotions, whereas the relations involving control were weaker and not always consistent with the hypothesized pattern. Most measurement properties and structural relations were broadly comparable across gender, study field, and HDI groups, and positive emotions were generally more frequent than negative emotions.

Overall, the results highlight the relevance of considering students' cognitive appraisals and emotional experiences together when examining generative AI in higher education. However, the cross-sectional, correlational, and convenience-sample design does not establish causal mechanisms, universal relations, or prescriptive implications. Future longitudinal and experimental research should examine how these associations evolve as generative AI systems and educational practices develop.

CRediT authorship contribution statement

Daniela Raccanello: Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Roberto Burro:** Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Giada Vicentini:** Writing – original draft, Visualization, Validation, Methodology, Investigation, Data curation, Conceptualization. **Aleksander Aristovnik:** Project administration, Funding acquisition. **Damijana Keržič:** Writing – review & editing. **Dejan Ravšelj:** Project administration, Funding acquisition. **Lan Umek:** Resources. **Nina Tomaževič:** Writing – review & editing.

Ethics declaration

Written informed consent to take part in the study and to publish the article has been obtained from all participants or their legal representatives. The privacy rights of participants have been observed.

This study was performed in compliance with relevant laws, regulatory frameworks and guidelines where the research took place. This study was approved by the University of Oran 1, Algeria; University of Nicosia, Cyprus; European University Cyprus, Cyprus; Polytechnic University, Ecuador; University of Verona, Italy; Yamanashi Gakuin University, Japan; University of Luxembourg, Luxembourg; Imam Abdulrahman Bin Faisal University, Saudi Arabia; University of Chester, United Kingdom; University of East London, United Kingdom. (Approval No. 03/CED/FACMED/2023; EEBK EII 2023.01.318; EEBK EII 2023.01.318; C-22; 2023_25; 23–010; ERP 23–101 StuPer ChatGPT SA/cd; IRB-2024-02-091 and IRB-2024-10-316; ASCHPR0211/23; ETH2324-0028)

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the authors utilized Grammarly and ChatGPT to enhance their writing by checking grammar, spelling, and punctuation, and suggesting clearer wording and style improvements. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Declaration of competing interest

The authors declare no conflict of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chbr.2026.101296.

Data availability

Data will be made available on request.

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