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Conceptual Paper

Generative AI Personalized Feedback and College Students' Learning Agency: An Analytical Framework Based on Self-Determination Theory

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Abstract

The advent of GAI systems such as ChatGPT has resulted in the accessibility of personalized feedback for higher education learners; yet, we understand very little about how such feedback impacts the development of those learners. This paper relies on the SDT theory in the formulation of an analysis framework linking three concepts: feedback quality (objectivity, usefulness, genuineness), need satisfaction (autonomy, competence, relatedness), and learning agency of college learners. Our central claims include that credibility in standard feedback models should be extracted and considered as a new moderator – AI trust; SDT's three needs work quite differently when the feedback source is a machine rather than a person; and AI trust functions as a gatekeeper that shapes how much feedback quality converts into need satisfaction. The model moves away from examining the effect of AI on learning outcomes towards examining whether AI might—or might not—cultivate genuinely agentic learners.

Keywords

Generative AI, Personalized feedback, Learning agency, Self-determination theory, AI trust, Higher education

1. Introduction

College learners are using GAI tools for feedback on writing, concept understanding, and study planning on a level that would have been unbelievable five years ago (Dai & Chai, 2024; Zhai et al., 2024). The feedback provided by ChatGPT-like tools is contextualized and takes up questions; at least intuitively, this seems to be highly personalized. Such changes make artificial intelligence feedback a pressing topic in educational technology, and with good reason: if these tools change learners' ways of studying, then we must understand how they

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work.

But the straightforward answer at present is that we actually do not know much about it. While it is obvious that some students get more out of the same feedback by AI than others, the difference cannot be attributed to mere differences in the quality of feedback. Instead, it is rather psychological processing and handling of the feedback received by students (Narciss, 2013; Hattie & Timperley, 2007). The three gaps found in the existing literature make it difficult to study this phenomenon. Firstly, studies on AI feedback hardly focus on the process variable but only consider the results variable like grades and performance (Ba et al., 2025). Secondly, studies on feedback quality and studies on learning motivation have been developing independently over the years without much interaction with each other (Ryan et al., 2019). Moreover, the issue of students' trust in the AI system, which is arguably one of the crucial factors influencing their engagement and participation, has not been formally incorporated into any explanatory model (Glikson & Woolley, 2020).

Self Determination Theory (SDT) can be said to be the best theoretical approach for filling these research gaps. According to SDT, motivation is not influenced directly by the external environment; rather, it is indirectly influenced by the satisfaction of certain psychological needs of the individual through the external environment. These needs include autonomy, competence and relatedness (Deci & Ryan, 2000). But here lies the issue because SDT itself was developed through human-to-human interaction. Hence, it is applied in understanding the interaction of feedback from people to AI and vice versa, which is not something that can just substitute ideas. Rather, it needs to reconsider the role of these psychological needs when there is a language model in the other end.

This paper creates an analysis structure by linking three main variables: quality of GAI feedback perception, satisfaction of basic psychological needs and dynamism of learning into a tri-level interpretive framework, as well as setting up the AI trust as a regulating boundary variable throughout the whole framework. This paper does not perform any empirical research. The aim of the paper is to develop a structure that will be theoretically founded and further tested empirically in the future.

2. Core Concepts

2.1. Perceived Quality of GAI Personalized Feedback

The dimensions of quality feedback used in education research usually consist of four elements: objectivity, usefulness, genuineness, and credibility (Ryan et al., 2019). In the case when feedback is given by human teachers, this approach works relatively well, as one of its components, credibility (competence and reliability of the feedback provider), is evaluated

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automatically together with the feedback itself.

The model continues to maintain objectivity, usefulness, and genuineness as the three qualities of feedback while breaking down the credibility aspect and reinterpreting it as trust in AI, which acts independently as a moderator.

In the case of GAI, the other three constructs take on different meanings. The meaning of objectivity in GAI is that the feedback given is related to the performance of the learner, as opposed to the template-based approach (Shute, 2008). In addition, usefulness means that the feedback given helps students understand the ways in which they can improve themselves (Narciss, 2013). Genuineness refers to giving feedback which makes students feel like the feedback has been genuinely based on their actual learning task or submission and not the general one which seems to apply to all (Nazaretsky et al., 2024).

In the context of personalized feedback from generative AI, the three dimensions above reflect the matching degree between feedback content and learners' specific performance as well as their psychological expectations.

First, objectivity rooted in procedural and informational justice theories emphasizes consistency between feedback and learners' real performance beyond factual accuracy and impartiality. In personalized scenarios, objectivity manifests as precision and specificity, meaning AI delivers fact-based evaluations targeting individual responses instead of generic templates.

Second, usefulness refers to how well feedback fits learners' improvement trajectories. Effective personalized feedback is highly relevant and applicable. It identifies errors and provides developmental cues rather than standard answers, catering to individual cognitive needs and guiding follow-up learning behaviors.

Third, genuineness captures the emotional tone and sincerity of feedback delivery. Personalized genuineness is reflected in sincere wording and non-mechanical evaluation. Since GenAI feedback is easily perceived as templated, context-rich expressions help learners feel feedback is earned from their own learning performance, rather than empty algorithm-generated compliments.

From learners' subjective perception, this study defines perceived quality of generative AI personalized feedback as a multi-dimensional construct including objectivity, usefulness and genuineness. Personalization is interpreted as a dynamic matching process between feedback and individual learner characteristics. This definition extends classic feedback quality dimensions to the GenAI context, integrates prior literature, and lays a theoretical foundation for analyzing how AI feedback shapes learning agency via psychological need satisfaction.Notably, the term genuineness here describes learners' perceived feeling rather than genuine human emotion owned by AI systems, which avoids anthropomorphic misinterpretation of machine algorithm output.

2.2. Learning Agency

Learning agency has gained much importance recently since it represents the way learners actively construct their own process of learning. According to OECD (2019), learning agency is defined as the capacity of learners to establish goals and make choices regarding their learning and be responsible for its results. Xia et al. (2025) define learning agency via three components: competency component which covers self-regulation and self-reflection, action component which encompasses engagement, accountability, and selective action, and psychological component which includes self-efficacy, intrinsic motivation, and volition.

In this research, learning agency serves as the outcome variable, rather than learning motivation or learning achievements. There is one reason for such approach – traditional measures of outcomes often fail to reflect learner's progress in time. While one may have high scores, he or she may rely more and more on artificial intelligence during the learning process. The problem of learning agency is different; the focus lies on the ability of learners to manage their learning process. With artificial intelligence becoming an inevitable part of higher education, it can become a valid way of measuring its effectiveness.

2.3. AI Trust

Trusting AI means the overall evaluation by the individual of the capabilities, dependability, and quality of the system's output when the individual lacks the opportunity to verify what the system is actually doing (Glikson & Woolley, 2020). Within this context, trusting AI would not result in learning outcomes on its own. It would rather serve as a filter whereby a distrustful student would fail to learn from even quality feedback, whereas a student having too much trust in the system might accept poor-quality feedback. Calibrated trust, which is sufficiently accurate to enable effective engagement and skeptical enough to retain independent judgment (Parasuraman & Riley, 1997), is what is important. We believe that reaching this level of calibrated trust in the students is equally a learning objective and a design problem.

3. SDT in the GAI Context: Where It Works and Where It Doesn't

The basic premise of self-determination theory can be summed up simply as the fact that autonomy, competence, and relatedness are conducive to intrinsic motivation, while their denial leads to disengagement (Deci & Ryan, 2000). How true this statement will be for the cases in which the feedback comes from an AI is still not known. Existing literature suggests that the applicability of the three needs may differ across dimensions rather than transferring uniformly to GAI-supported learning environments.

Autonomy seems to be the need that depends on conditions the most. The information from the GAI is given in a form of recommendations, not orders, while students can choose for themselves when, how often, and to what degree they want to communicate with the system. Such features could foster perceptions of autonomy by ensuring students' freedom of choice (Chiu, 2023). However, constant use of such evaluations made by artificial intelligence might decrease these opportunities. As time passes, there will be some users who will start to rely on outside advice instead of developing an independent ability to judge and assess their work. That is why autonomy satisfaction will depend more on the learner's pattern of behavior than on the technical aspects of the system. Those who think about AI assistance critically are likely to experience greater autonomy than those who accept recommendations without reflection.

The need for competence seems to align most closely with the current capabilities of GAI technology. The advantage of using AI in feedback lies in the ability of the system to adapt explanations and assistance depending on the knowledge level of learners. An idea can be explained to beginners in one way and to advanced students in another, and feedback can be improved constantly based on performance (Dai & Lai, 2024). This sort of adaptive assistance aligns with the conditions under which competence satisfaction can be achieved. Progress would seem more obvious when tasks are not impossible but challenging. The efficacy of this approach relies mainly on the appropriateness of the feedback relative to learners' skill level. Simple feedback provides little development opportunities, while too hard feedback might frustrate them.

Relatedness presents the greatest theoretical challenge of the three. It is typically characterized within SDT as the emotional state of care, acceptance, and connectedness experienced in interpersonal relationships (Baumeister & Leary, 1995). AI systems cannot deliver genuine interpersonal affection, yet customized feedback marked by high genuineness may help learners feel their unique situations acknowledged. If feedback is tailored to individual learners' performance rather than generic templates, learners may interpret it as thoughtful assistance and care. Such reasoning aligns with evidence that people socially engage with computational agents (Reeves & Nass, 1996). Within this framework, such algorithmic contextual support can temporarily foster relatedness satisfaction without face-to-face human contact. Nevertheless, unlike early rigid computer interfaces, modern

LLMs generate fluent conversational feedback; it remains unclear whether perceived genuineness from algorithmic outputs forms equivalent relational attachment, or merely creates a fleeting illusion of interpersonal support. Once learners recognize warm, targeted feedback stems from preset program logic rather than spontaneous human concern, the positive link between feedback genuineness and relatedness satisfaction will weaken drastically, which also accounts for AI trust's strongest moderating effect on this pathway.

From the above discussion, it is clear that the three main psychological needs do not work in the same way in GAI learning environments. It seems that the need for competence is strongly linked to feedback provided through AI. The need for autonomy is highly dependent on learners' own involvement, whereas the need for relatedness demands rethinking of social support. The distinctions offer a crucial reason why AI trust should form one of the core boundary conditions within the model since it may have differential impacts on each of the three ways.

4. The Integrative Analytical Framework

4.1. Overall Structure

Figure 1 depicts the theoretical framework that has been formulated in this research. The theory rests on SDT and discusses the possible manner in which the perception of GAI feedback can result in the formation of learning agency among students. The concept of AI trust has been integrated into this framework as a boundary condition.

This theoretical model comprises three layers that are interrelated. The first one involves perceived feedback quality and consists of three factors: objectivity, usefulness, and genuineness. These factors denote the perception and evaluation of feedback delivered by GAI systems from the perspective of learners. In this case, AI trust becomes an intervening variable that does not impact learning outcomes directly but influences the way learners interact with the feedback.

The second level involves the psychological processes beneath. Using the insights of SDT, the model assumes that varying dimensions of the quality of feedback serve as means for fulfilling the basic needs for autonomy, competence, and relatedness. The third level involves learning agency. In the current model, the concept of learning agency refers to a developmental phenomenon which emerges when there is continuous support of learners' basic needs. The expression of the latter can be seen in behavior, competency development, and psychological factors of self-regulation.

To facilitate future empirical testing of this theoretical framework, this paper puts forward testable core propositions:

Proposition 1: Perceived feedback objectivity positively predicts competence need satisfaction and indirectly boosts autonomy satisfaction.

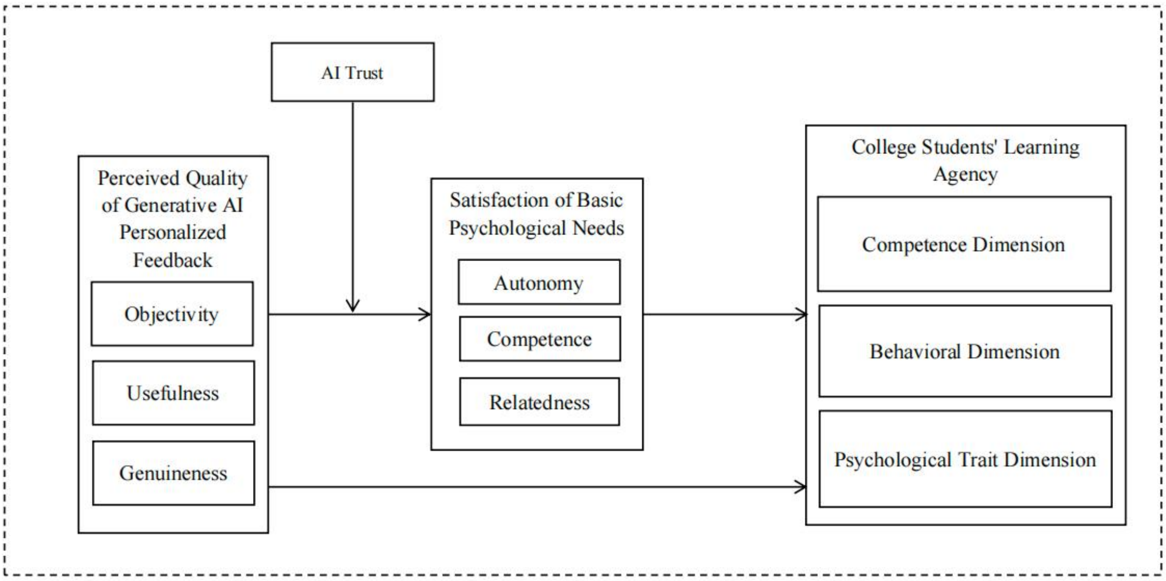
Proposition 2: Perceived feedback usefulness positively predicts both autonomy and competence need satisfaction.

Proposition 3: Perceived feedback genuineness positively predicts relatedness need satisfaction.

Proposition 4: AI trust positively moderates all three pathways, and its moderating effect is the strongest on the genuineness–relatedness linkage.

Figure 1

An Integrative Framework of GAI Personalized Feedback and Learning Agency



4.2. How Feedback Quality Connects to Psychological Needs

Table 1 shows how the three feedback quality dimensions correspond to the three psychological needs. The first dimension has its corresponding main target, but it also influences another need, hence the reason for treating the relationship as interrelated rather than being parallel.

Table 1

Linkage Structure Between Perceived Feedback Quality Dimensions and Basic Psychological Needs

Dimension	Primary Need	Secondary	Core Mechanism
Objectivity	Competence	Autonomy	Grounds capability cognition in actual performance; supports evidence-based self-assessment

Usefulness	Autonomy + Competence	—	Improvement cues open exploration space without prescribing answers; clarifies development pathways
Genuineness	Relatedness	—	Contextually responsive tone signals being attended to, partially substituting for interpersonal care

Note. AI trust moderates all three pathways; its effect on the genuineness–relatedness linkage is the strongest.

Objectivity is most directly linked to competence satisfaction. Feedback that truly indicates a learner's performance gives an adequate ground for assessing his or her competencies and weaknesses (Shute, 2008). It allows for a better assessment of a learner's competence level and knowledge gaps. Lack of objectivity in feedback makes it difficult for a learner to assess his or her own performance level; this can have a negative impact on the competence satisfaction level. Objectivity plays a role in enhancing autonomy through making better-informed decisions based on one's true abilities.

Usefulness is associated with both competence and autonomy. Feedback that specifies areas that require improvement and provides relevant instructions enhances competence as learners get to know the feasible ways of improving their performance (Hattie & Timperley, 2007). On the other hand, feedback that directs but does not provide one definite way of doing things ensures that learners remain autonomous in their actions (Narciss, 2013). However, feedback that only serves to point out the weaknesses of learners without showing them what can be done next may make learners feel confused about how to move forward. Consistent experience of such situations may lead to a loss of control and motivation among learners.

Genuineness has mostly to do with the fulfillment of relatedness. If the learners feel that the feedback is paying heed to their unique situation, then they will be able to feel supported and recognized. But the strength of this path will largely depend on the degree of AI trust. Those learners who trust more may interpret personalized feedback as a sign that their unique requirements are recognized. Students who are skeptical about the system are more inclined to view the feedback as arising from standardized algorithmic operations and not responsive operations (Nazaretsky et al., 2024). In such an environment, the presence of sincere statements will have little impact on the satisfaction with relatedness since they will be seen as stylistic elements of the system.

4.3. From Need Satisfaction to Learning Agency

The fulfillment of psychological needs is not necessarily a guarantee for the establishment of learning agency. It acts rather as a basis for such development on a psychological level. In the suggested theoretical model, autonomy, competence, and relatedness are linked to various aspects of learning agency, though their connection is still very close.

The fulfillment of autonomy is mostly related to the action component of agency in learning. Students who consider their choices as self-endorsed choices will be more prone to taking the responsibility of the consequences, strategic allocation of effort, and active involvement in the learning process (Ryan & Deci, 2000; OECD, 2019). Excessive use of AI suggestions may limit chances of making independent choices. With time, students may become less experienced in evaluating options and making judgments personally.

Competence satisfaction will contribute to the competency aspect due to the creation of self-efficacy. Due to the fact that the learners get better with time during the process of receiving feedback, they become more assured about their ability to handle the challenges in their learning process. High levels of self-efficacy motivate the learners to set goals for themselves, monitor themselves and modify the learning approaches whenever necessary (Bandura, 2001; Zimmerman, 1998). Where competence needs are not met, the learners may be more inclined to rely on AI as an alternative for hard work.

The relatedness needs satisfaction seems to be closely linked to the psychological dimension of learning agency. In turn, the perceptions of support and recognition may decrease uncertainty and enable the students to stay motivated amid problems at school (Baumeister & Leary, 1995). There is also interdependence between the three need-satisfaction channels. The more competent learners are, the more capable they become of being autonomous and taking actions. On the other hand, autonomous activities provide new chances for learners to become competent. Support perceptions give the emotional basis for these processes. Thus, the development of learning agency is dependent upon the joint action of the three needs.

4.4. The Role of AI Trust

AI trust plays a role at two different levels within this framework. In the information processing stage, it affects whether the student interacts with the feedback in such a way that it reaches the psychological mechanism stage. For instance, a student who receives feedback from the AI with suspicion will end up filtering the feedback as noise and thus will derive little satisfaction of his or her needs. On the other hand, a student who blindly believes what is said by the AI risks feeling competent in situations where there is no actual competence, or may defer to AI judgment in ways that gradually erode autonomy (Lee & See, 2004). Too little and too much trust is wrong; the right level of trust is not high or low—it is accurate.

However, at the individual-level pathway itself, trust is not a moderating factor that affects the satisfaction of all the three needs equally. While relatedness is highly sensitive to trust, because it depends upon the need to be truly cared for and therefore is very vulnerable to any doubts that warmth is nothing but a preprogrammed response, competence is relatively more insensitive.

The autonomy pathway is somewhat in-between, depending on whether the user's behavior is critical or deferential, for example. In order to study these models using empirical research methods, relying on one single measure of AI trust for all paths would probably be misleading (Parasuraman & Riley, 1997). Scholars identify AI trust as a two-dimensional construct including cognitive and affective trust (Glikson & Woolley, 2020). Cognitive trust represents rational evaluation of system reliability, whereas affective trust captures perceived benevolence from interactions. The two dimensions function simultaneously in practice, which means measuring AI trust with a single unified indicator will produce biased results. Future empirical studies should compare unidimensional and multi-dimensional trust structures to test the model.Different measures are needed for each pathway.Furthermore, maladaptive feedback such as AI hallucinations and over-guidance, together with blind or zero trust, break the positive transmission chain. Only calibrated trust enables balanced screening and absorption of AI feedback to foster learning agency.

4.5. What This Framework Contributes

This suggested model makes a number of contributions to the literature. Firstly, the contribution can be seen in the combination of the studies on feedback quality and theories of motivation – domains that usually proceed in different ways. In terms of considering feedback quality not from the point of view of its features but from the perspective of learners' perception of it, this model allows us to focus on the psychological processes by means of which feedback perceptions affect learning outcomes.

Another contribution is that of choosing the learning agency as the key dependent variable. The bulk of the current literature on learning with the help of AI concentrates on measuring performance through various measures like grades or successful task completion. However, this measure is still one-sided in terms of understanding the educational consequences of using AI. Learning agency refers to the ability of the learner to control, manage, and take ownership of his/her own learning process. As AI systems continue to be incorporated into education environments, one interesting question that arises is how these systems relate to learner independence.

Another contribution is that of the concept of AI trust in the framework. Instead of

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considering trust as a general moderator, the framework suggests that the effect of trust can differ depending on the pathway—autonomy, competence, or relatedness. This distinction makes a difference not only theoretically but also empirically. This indicates that future research might gain from studying the influence of trust based on specific pathways rather than solely through global indicators. This would give a clearer perspective of how trust influences the interaction between learners and GAI's feedback and subsequent psychological mechanisms.

5. Discussion

5.1. What the Framework Does Not Yet Resolve

Like any conceptual model, the present framework simplifies a more complex reality and therefore leaves several questions open for future investigation.

The first one has to do with the model of the structure of the perception of feedback quality. While objectivity, usefulness, and genuineness have been named as the crucial aspects, it is not clear whether they retain equal weight in all learning situations. Learners face different challenges in different subjects. Where individual expression is important, the attention and responsiveness of the feedback will be especially valued. On the other hand, well-defined courses may attach more importance to accuracy and evaluative assessment based on facts. Further research is required to identify if the suggested structure holds good in different situations or needs modification according to the academic discipline.

Uncertainty is also present when it comes to how AI feedback impacts relatedness satisfaction. The model relies on the idea that customized feedback can lead to feelings of support regardless of the lack of face-to-face contact with other people. Although past research demonstrates that people tend to engage with technology in a social manner (Reeves & Nass, 1996), it is unknown whether or not it operates like inter-personal connections. These learners will vary widely in terms of their perception and engagement with the AI system, which might have an effect on the power of the relatedness pathway. It is vital to explore these variations in the future.

Another limitation lies in the way trust is treated. In order to make the theoretical approach to AI trust more clear-cut, it is described as a fairly stable moderator. In practice, though, the concept of trust could evolve through multiple contacts and vary based on the learner's experience. Due to the changing nature of this characteristic, the effect of trust could be different in various stages of learning with the help of artificial intelligence. Using longitudinal studies will result in a more detailed analysis of trust development and its impact on the proposed relations.

5.2. What This Means in Practice

Implications arise from this conceptual framework. Most importantly, the learning benefits to be gained from feedback provided by the GAI systems are determined not only by the performance of such systems but also by how their users interpret and utilize such feedback.

For feedback to help the learner learn better, it needs to have the specific features of the learner's own work instead of being based on generalized information. This can be made possible by offering adequate context and making learners interact meaningfully with the system, which will enhance the quality of the feedback. However, the learners also require guidance on how to engage with the feedback offered by the AI. Learners who use GAI only for finding solutions may gain less than learners who explore other options.

The theory also emphasizes the significance of AI literacy. Trust seems to be playing an important part in the process of deciding how feedback affects the satisfaction of psychological needs, but effective trust cannot be either blind trust or distrust. It is possible that educational establishments will have to assist learners in developing a better-informed awareness of how GAI systems function, their capacities, as well as their limitations. This awareness can motivate learners to use these technologies more thoughtfully.

For practical application, writing and STEM courses can adopt this framework: teachers design AI feedback verification tasks to cultivate calibrated trust, prevent over-reliance and develop learners' autonomous judgment.

6. Conclusion

The increase in the use of GAI in the realm of higher education has raised new issues regarding student involvement in learning and their development as learners. Apart from the role that it plays as an instructional tool, the feedback from GAI may also impact the psychological mechanisms that affect students' ability to learn independently. This paper provides an understanding of such influence using the interaction between the quality of feedback, psychological needs satisfaction, and GAI trust.

There are also several issues that can be considered for future research within this conceptual framework. Future studies should aim at investigating the stability of the suggested dimensions of feedback quality in different domains, the development of feelings of relatedness in AI-enhanced learning situations, as well as the formation of trust through multiple interactions with GAI. These factors still matter greatly when it comes to the educational impacts of AI-assisted learning in the long run.

The growing popularity of GAI means that assessing its value as an educational tool should involve looking not just at immediate educational results but also at the possible impact of GAI on learners' autonomy, competence, and self-regulation skills. Such knowledge might be useful for determining how AI systems promote sustainable development of learners.

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Author contributions

Conceptualization, X.C. and A.H.; methodology, X.C. and A.H.; formal analysis, X.C.; investigation, X.C.; writing—original draft preparation, X.C.; writing—review and editing, A.H.; visualization, X.C.; supervision, A.H. All authors have read and agreed to the published version of the manuscript.

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The authors declare that there is no conflict of interest.

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Consent to participate

Not applicable.

Consent for publication

All authors have given their consent.

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