Let Me Explain: Linking Situational Interest to Student Response in Interviews

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Abstract. This study investigates how situational interest (SI) influences student interview responses during game-based learning. Using real-time interviews conducted within the What-If Hypothetical Implementations in Minecraft (WHIMC) environment, we analyzed differences in discourse between high- and low-SI students. Interview transcripts were coded using a structured codebook through a hybrid approach combining humans and GPT-4o. Epistemic Networks of student reflections revealed that high-SI students were more likely to offer *Brief* and *Enthusiastic* responses across all question types. These students used excited language, reacted aloud to game events, and expressed interest in specific gameplay elements. Low-SI students provided more *Explanatory* and *Neutral* responses. They often paused to describe their plans, explain in-game decisions, or reason through moments of uncertainty. Ordered Networks of interviewer statements revealed that interviewers' strategies remained consistent for low- and high-SI groups, ruling out interviewer behavior as the cause of differences in student responses. These results shed light on the ways student interest levels may impact interview responses during game-based learning experiences.

Keywords: Situational Interest, Game-based Learning, Epistemic Network Analysis, Real-Time Interviews

1 Introduction

Situational interest, characterized by short-term engagement that is typically triggered by external stimuli within educational settings [15], often plays a critical role in learning [8]. When situational interest emerges, students tend to exhibit heightened attention and emotional engagement, which in turn promotes deeper involvement with the learning material. As situational interest often arises in response to specific features within the environment [22], researchers have long sought to understand not only how this form of interest is triggered, but also how it shapes students' perceptions and reflections as they engage with different learning contexts.

Game-based learning (GBL) has been recognized as particularly effective in fostering students' interest, mainly due to the immersive, interactive design of many learning

games and the inherently motivating nature of gameplay for students [11,20]. Prior research has explored how situational interest shapes students' learning experiences during gameplay (e.g., [11]). However, few studies have examined how students describe their learning when experiencing situational interest in real time (e.g., sharing their thinking, reacting to unfolding events, or shifting focus during gameplay).

Interviews offer researchers an opportunity to understand how students make sense of their gameplay experiences, express spontaneous emotional reactions, and explain the rationale behind their in-game actions (e.g., [27]). Because students' foci and emotional response can shift rapidly during gameplay [30], moments of situational interest may be more difficult to recall or articulate after a session has ended. Real-time interviews are therefore particularly useful for capturing students' immediate reactions and thought processes, such as where they direct their attention, what they find interesting or challenging, and how they interpret or respond to unfolding events. Targeted interviews also allow for more probing into student reasoning compared to other common approaches such as concurrent think-aloud protocols (e.g. [14]). Through analysis of real-time interview data, researchers can gain valuable insight into how situational interest dynamically shapes students' cognitive engagement (e.g., reasoning behind their decisions), and emotional engagement (e.g., feelings associated with specific in-game activities or events). Despite the value of real-time interviews for capturing students' unfolding thought during gameplay, less is known about how situational interest shapes these responses and expressions. This gap, in turn, subtly limits researchers' ability to interpret student moment-to-moment explanations and emotional reactions as reliable signs of engagement and learning in game-based learning environments.

To investigate this, the study analyzes real-time interviews conducted as students engaged with the What-If Hypothetical Implementations in Minecraft (WHIMC) learning environment—an immersive, game-based platform designed to cultivate students' interest in STEM ([12,13]). Specifically, we used Epistemic Network Analysis (ENA) to investigate the research question: How do students with high and low situational interest differ in their interview responses during game-based learning? To support this analysis, we utilized a large language model (LLM), GPT-4o, to assist with qualitative coding, comparing how the content and structure of students' discourse patterns vary based on their self-reported interest levels.

2 Related Work

2.1 Situational Interest

Interest is commonly categorized into two forms: individual interest and situational interest [9]. Individual interest refers to a long-term, internalized form of interest, whereas situational interest is characterized as a short-term, context-dependent form of interest. While the two forms of interest are conceptually distinct, situational interest is often considered a critical precursor to the development of individual interest and knowledge gains [22]. Accordingly, researchers have investigated how situational interest can be intentionally fostered through learning experiences, as well as its impact on students' later engagement and learning outcomes. For example, Abas et al. reported a positive

correlation between students' situational interest and their emerging individual interest in the context of online language learning [1]. Additionally, Subramaniam found that situational interest can serve as a motivational catalyst for student engagement and can be fostered through thoughtful adjustments to learning tasks, instructional strategies, and the design of the learning environment [25]. More recently, Wei et al. explored how students' levels of situational interest differ based on the content of the observations they recorded during gameplay, finding that students with high interest tend to generate more observations and are more likely to reference science-related concepts than their low-interest peers [28]. Despite these ongoing efforts, fewer studies have explored differences in how students with different levels of situational interest might perceive and interpret their learning experience.

2.2 Interview Approaches

While research has explored how interest impact students' learning outcomes or behaviors, less is known about how students verbally express interest in real time. Interviews, particularly those conducted during gameplay, offer a valuable lens to explore how interest-driven learning is reflected in students' discourse as it unfolds. Interviews are a widely used research method that allow researchers to engage directly with participants and collect valuable qualitative data on their perspectives and lived experiences [21]. In educational contexts, interviews are often used to collect a variety of information from students, such as their thought processes or self-perceptions—dimensions that are difficult to capture through observation or performance data alone (see [5]). Despite the value of interview-based approaches, most interviews have traditionally been conducted either before or after learning activities (e.g., [23]), which limits their ability to capture students' immediate reactions and in-the-moment reasoning as they emerge.

Recently, a more adaptive interview technique—Data Driven Classroom Interviews (DDCIs)—has been introduced to help researchers access student thinking as it evolves in real time [2]. DDCIs are designed to facilitate brief, strategically timed interviews during active engagement in learning environments where students are immersed in interactive tasks. DDCIs are supported by a tool called Quick Red Fox [10], an open-source application that detects pre-specified indicators of interest-related behaviors that triggers interviewers to engage with students at relevant moments. By guiding timely conversations at key points during learning, QRF enables researchers to gather rich, contextualized data on students' perceptions, affective engagement, and reflections as they occur. In doing so, the system supports researchers in delivering timely, targeted responses aligned with students' emerging learning needs.

2.3 Analyzing Interviews with Epistemic Network Analysis

Epistemic Network Analysis (ENA), an analytical method that models the structure of connections among coded elements in discourse data, has been widely adopted by scholars in the Quantitative Ethnography (QE) community [24] to visualize and quantify patterns of interaction over time. Though ENA was initially applied to game and

simulation-based learning datasets [18], and later used to examine interest and motivation in game-based learning [3], researchers have more recently applied ENA to analyze interview data, revealing how ideas are expressed and connected over time in both collaborative and one-on-one conversational settings. For example, Cheung and Winterbottom employed ENA to analyze semi-structured interviews, examining how students with varying levels of competence visualized and processed textbook visual representations as part of their understanding [6]. In addition, Orrill and Brown analyzed both think-aloud and face-to-face interviews to develop a theoretical model of how teachers with varying levels of expertise drew on their knowledge resources [19]. These studies underscore ENA's value in capturing the complexity and dynamics of interview discourse, providing a powerful lens for understanding how meaning is constructed through verbal interaction. Despite this growing body of work, ENA remains untested as a tool for assessing how interview discourse varies as a function of students' situational interest during game-based learning.

3 Methods

3.1 Data Context

The dataset used for this study was collected from a five-day, after-school summer camp held in the northeastern United States in 2024. As part of the camp activities, students had the opportunity to engage with a digital learning environment—What-If Hypothetical Implementations in Minecraft (WHIMC; [12]), a STEM-focused simulation built within Minecraft Java Edition. WHIMC is designed to promote students' interest in science, technology, engineering, and mathematics (STEM) by immersing them in interactive, astronomy-related scenarios that encourage exploration of hypothetical conditions in space ([13]). Within the game, there are multiple virtual scientific tools available for students' use. For instance, students could employ measurement tools to record temperature variations on Mars and Earth or monitor changes in oxygen level when two planets drift too close or too far apart. Beyond these investigations, WHIMC also encourages students to engage with a range of open-ended scientific inquiries, such as "*What if Earth had no Moon?*", "*What if Saturn were twice its current size?*", or "*What would it take to mine an asteroid?*".

During the camp, two researchers, along with other educators and facilitators, were present each day to engage with students and conduct one-on-one, semi-structured DDCIs as students actively engaged with the gameplay. The two researchers approached students individually and conducted brief interviews (approximately five minutes each) with individual students throughout the day. To ensure the consistency of purpose and maintain a shared focus across sessions, all interviews followed a guiding protocol that included a set of pre-developed questions and topic areas (e.g., Minecraft gameplay, astronomy knowledge, etc.). DDCIs were initiated using the QRF app, which monitors student in-game actions and alerts interviewers when important triggers —pre-defined student actions that researchers identified and associated with potential learning and interest—occur. For example, a player using ice blocks to build their Mars

base might trigger an interview in WHIMC, as it suggests that a student may have applied prior knowledge shared in the camp about insulating materials. DDCIs using QRF allowed the interviewers to balance interviews across students while prioritizing rare or important events. All interview sessions were audio recorded for further analysis.

A total of 14 students participated in the camp, with 10 male, 3 female, and 1 who self-identified as non-binary. The students represented a mix of racial and ethnic identities: 8 White Americans, 2 Asian Americans, 1 European, and 3 students who preferred not to disclose identities. Participation was voluntary, with assent obtained from the students and informed consent from their guardians at the beginning of the camp.

After completing all interviews, a researcher team processed the data for analysis. Each interview recording was transcribed by an experienced professional for accuracy and clarity. A standardized transcription protocol was followed for all interviews, in which both students and interviewers were de-identified and the data were segmented by individual utterances to preserve the chronological flow of the conversation.

3.2 Measuring Situational Interest

For all 14 students, we collected measures of situational interest (SI) on the fourth day of the camp, using a validated survey based on the work of Linnenbrink-Garcia et al. [15]. Each student's SI score was then calculated as the average of their responses across all items on the scale. Based on their SI scores, students were categorized into high (n=6), low (n=4), and medium (n=4) interest groups according to the bottom, middle, and top thirds of the interest score distribution. This tercile approach allowed us to create balanced groups while also achieving a strong contrast between the high- and low-SI groups. To align with our research question, we focused our analysis on differences in interview responses between students in these two groups, excluding those who fell into the medium group. This procedure resulted in a total of 10 students being included in the final analysis.

3.3 Codebook Development

We developed the codebook using a thematic analysis approach outlined by Weston et al. [29]. A researcher first inductively reviewed a subset of the interview transcripts, including sessions with students from both high- and low-interest groups, as well as interviews led by both interviewers to achieve balanced representation across participants and interviewers. Following a close examination of the data, the same researcher then engaged in an iterative process of identifying, analyzing, and refining emerging codes grounded in the data, with feedback from the broader research team. This iterative process led to the development of a codebook, which comprised of two main code categories: (1) Question Types, representing the kinds of questions interviewers/researchers used to approach and interact with students; and (2) Response Types, encompassing different forms of responses from interviewees/students.

Table 1. Codebook for interviewer questions with examples.

Codes & Definitions	Examples
Open-ended Question: encourages students to provide an elaborative or reflective response rather than a brief or one-word answer.	Interviewer: *What do you like about it?*
Close-ended Question: prompts students to provide a brief, specific response, often limited to a single word from predefined options, such as 'YES' or 'NO'. Typically seeks factual answers or confirmations rather than encouraging further explanation.	Interviewer: *Were you able to place objects before?*
Follow-up Question: prompts students to expand on their initial responses, clarify their reasoning, or delve into their thought processes more deeply.	Interviewer: *Did he morph into an owl?* Student: *Yes, he is Duolingo.* Interviewer: *What is he doing as Duolingo?*
Process/Strategy Question: prompts students to describe their thought processes, actions, decision-making, or strategy use while engaging in a task.	Interviewer: *So, what's your strategy for blowing up Saturn?*
Reframing/Restating Students' Statement: the interviewer restates part of the student's original statement by repeating a key phrase, rewording the sentence, or echoing the last word to check for correct understanding.	Interviewer: *Are the days warmer?* Student: *There are no days, it's …* Interviewer: *Oh, there's no days. Ohhh.*

Table 2. Codebook for student responses with examples.

Codes & Definitions	Examples
Explanation: responses that provide reasoning, clarification, or a detailed description of their thinking, actions, or decision-making process.	Interviewer: *Why did you decide to put that deeper underground?* Student: *Because I wanted to, and there's less radiation. So, you don't want radiation exposed. I mean that's why I'm wearing a hazmat suit."*
Enthusiastic Responses: responses that convey excitement, joy, or are associated with other positive reactions. Often includes playful language, expressive tones, or positive affective markers.	Interviewer: *Snow?* Student: *And a pressure plate. Whee!*
Brief Responses: students provide a short reply to questions, usually containing minimal elaboration; consist of a single word or a short phrase that directly addresses the question without expanding on the thought process.	Interviewer: *That armor; have you seen that before?"* Student: *Nah*
Neutral: responses do not clearly reflect enthusiasm or are short in length, these responses usually serve to confirm something, or make a factual statement, without	Interviewer: *What material is that?* Student: *It's black concrete.*

signaling interest or disinterest. They are typically moderate in tone and lack strong emotional expressions.	
Redirect: Students shift their focus away from the original question asked by the interviewer, instead of directly addressing the inquiry. Often unrelated or only loosely connected to the questions asked.	Interviewer: *like, what separates a computer from a robot?* Student: *Okay, I'm starting the underground section.*

3.4 Coding Procedures

The coding process in this study involved both human coding and automated coding with GPT-4o. Two researchers with training and experience in qualitative coding used the codebook to independently apply the codes to a subset of interviews. Question-type codes were applied only to interviewer turns, and response-type codes only to student turns; within each category, multiple codes could be assigned to a single utterance.

Inter-rater reliability (IRR) between the two human coders was checked using Cohen's kappa after an initial round, with several codes receiving an acceptable IRR at this stage ($\kappa>0.7$). Codes below this threshold then underwent social moderation [7], where two researchers discussed and consolidated similar codes, before a second round of coding to re-check IRR. Due to the large size of this dataset (~7000 utterances), we followed an emerging practice in the QE community of leveraging LLMs to automatically apply human-validated codes, a practice which has demonstrated reliable alignment with human-coded data across multiple contexts (e.g., [16,31]). To assess the reliability of GPT-4o in automating the coding process for this study, human-coded data were used as ground truth to evaluate the model's alignment with human coders. We used a few-shot prompting approach with the temperature hyperparameter set to 0 to produce consistent outputs across runs. GPT-4o was able to automate six codes that successfully achieved adequate IRR (i.e., $\kappa>0.7$, see Table 3). Additionally, each set of data was processed three times under identical configurations, with a majority vote used in cases where outputs differed across runs. We followed the prompt used in [16].

As Table 3 shows, GPT-4o struggles with codes that require contextual judgment from the surrounding dialogue (e.g., the preceding question or the subsequent response). For example, identifying whether a student is redirecting the conversation requires knowing whether their response shifts the topic away from the interviewer's question. Specifically, GPT-4o did not achieve acceptable agreement with human coders with three codes from the interviewer's question set (*Follow-up*, *Reframing*, and *Process;* see Table 1) and one code from the students' response side (*Re-direct*; see Table 2), as it was unable to replicate these judgements even with that context provided (i.e., $\kappa<0.7$). These categories were thus human coded.

Table 3. Inter-rater reliability between human-human (after final IRR check) and human-GPT.

Code Category	Codes	Final Coding Approach	Human-Human Kappa	Human-GPT		
				Kappa	Precision	Recall
Interview Question	Open-ended	GPT-4o	0.89	0.82	1.00	0.73
	Close-ended	GPT-4o	0.81	0.75	0.83	0.71

	Follow-up	Manual	0.78	0.57	0.45	1.00
	Process	Manual	0.78	0.50	0.44	0.78
	Reframing	Manual	0.75	0.47	0.38	0.75
Interviewee	Explanation	GPT-4o	0.82	0.78	0.73	0.89
Response	Brief	GPT-4o	0.80	0.79	0.79	0.93
	Enthusiastic	GPT-4o	0.89	0.75	0.71	0.83
	Neutral	GPT-4o	0.72	0.78	0.86	0.86
	Re-direct	Manual	0.76	0.39	0.35	0.82

3.5 Analytical Methods

To better understand how situational interest (SI) relates to student interview behaviors, we utilized the Web ENA Tool (version 1.7.0; [17]). We set students' interest level (high vs. low) as the primary unit variable subset using each student's unique player ID. Conversations were defined as all lines of data within a single interview. This reflects the structure of data collection, during which students were interviewed multiple times throughout a day based on triggers, with each interview being short in duration (lasting approximately five minutes) with pauses of varying lengths in between. Given the brief and continuous nature of discourse in the interviews, we selected an infinite stanza window. We believe ENA is a suitable method for exploring our research question because it accounts for code co-occurrences within the same line of data, allowing us to capture students' responses that reflect multiple codes simultaneously (e.g., a response that is both *Brief* and *Enthusiastic*). Moreover, while all question and response codes were included in the model, we used the Code Masking feature in the Web ENA tool to specifically highlight the connections between interviewer questions and student responses. In other words, the epistemic networks capture how students responded to interviewer prompts and how they elaborated on or shifted their ideas across utterances.

We also used Ordered Network Analysis (ONA; [26]) to examine whether the observed differences in high- and low-SI students' interview patterns may be due to variations in how interviewers structured their questions and interacted with students. ONA offers a valuable analytic lens for modeling interviewer strategies by capturing the strength and direction of connections between codes. Leveraging this affordance, we kept unit variable, conversation variable, and stanza window choices consistent with the epistemic networks, but included only Question Type codes in the model, as this enabled us to specifically focus on the order and types of questions interviewers asked. In both cases, a means rotation was applied to maximize variance along the x-axis.

4 Results

4.1 High vs. Low SI: How Interview Response Patterns Differ

Figure 1 displays the epistemic network for the high-SI group (See Fig. 1, *left*) and the low-SI group (See Fig. 1, *right*). Figure 2 displays a difference model that shows line weight (lw) differences that exceed 0.03 (See Fig. 2). A Mann-Whitney U test between

the networks for the two SI groups along the X-axis (U=19, p=0.03, effect size of r=-0.90 at α=0.05), found the differences to be statistically significant. Table 4 provides the corresponding lw(s) for each network. For visual clarity, all the unit circles are set equally spaced.

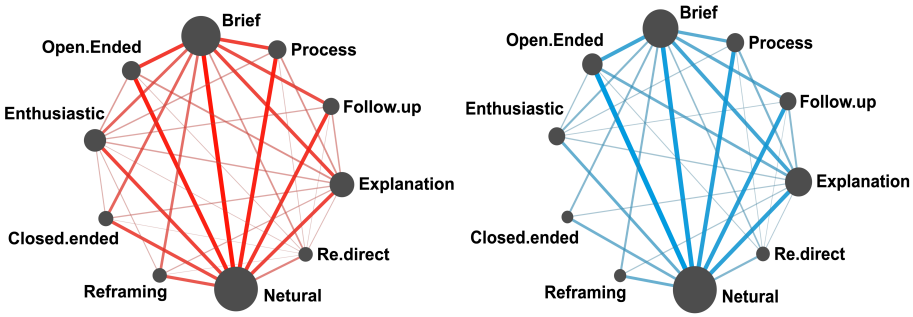


Fig. 1. ENA models for the high-SI group (red, *left*), the low-SI group (blue, *right*)

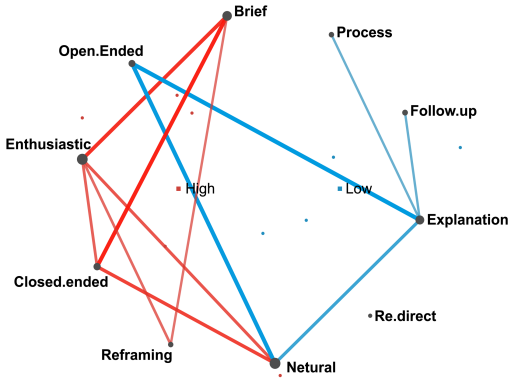


Fig. 2. Epistemic network showing the difference between high- and low-SI groups

Table 4. ENA Line weights, only line weights differences higher than 0.03 are shown.

Connection		High-SI Group (lw)	Low-SI Group (lw)	Differences
Follow-up	Explanation	0.10	0.13	-0.03
Open-ended	Explanation	0.12	0.18	-0.06
Open-ended	Neutral	0.28	0.34	-0.06
Process	Explanation	0.12	0.15	-0.03
Neutral	Explanation	0.23	0.28	-0.05
Neutral	Enthusiastic	0.23	0.19	0.04
Neutral	Close-ended	0.22	0.17	0.05
Reframing	Brief	0.18	0.14	0.04

Reframing	Enthusiastic	0.07	0.00	0.07
Close-ended	Brief	0.19	0.14	0.05
Close-ended	Neutral	0.22	0.17	0.05
Close-ended	Enthusiastic	0.07	0.00	0.07
Enthusiastic	Brief	0.19	0.14	0.05

In the difference model for high and low SI groups (Fig. 2), both the high- and low-SI groups exhibited two connections involving *Neutral* responses. This suggests that students across both groups commonly engaged in confirmatory or fact-based statements during gameplay interviews, such as offering an observational response to the researcher's question (e.g., *"I'm in the moon village"*), or narrating in-game events aloud (e.g., *"Rotational period"*). However, while *Neutral* responses were present across both groups, they co-occurred with different types of responses. Upon reviewing the interview data, *Neutral* responses were sometimes paired with *Enthusiastic* responses among high-SI students, such as a student might first describe their plan in a neutral tone: *"I'll go to the, um…"*, and then express excitement while carrying out the action: *"Hahaha! I am crouching."* On the other hand, *Neutral* responses from low-SI students were more often connected to *Explanation*. For example, when the interviewer asked a student how long they had worked on the farm, some students began with a neutral response: *"Not too long."*, and then followed with a detailed explanation of their plan: *"I think I'm get, we're gonna, like, I think, like, one row should be potatoes, another row, like, carrots or beets, and then, like, wheat and ..."* These differences in co-occurrence patterns suggest that while both groups offer *Neutral* responses during interviews, high-SI students may be more emotionally expressive in the moment, whereas low-SI students tend to engage in longer verbal explanations.

Despite this shared *Neutral* code, these students' broader interview patterns revealed meaningful differences. Among high-SI students (in red), *Brief* (e.g., *"Yeah."*) and *Enthusiastic* responses (e.g., "*Bees! I love bees"'*) are the two most connected codes. In contrast, low-SI students (in blue) exhibited stronger connections around *Neutral* (e.g., "*Yeah, a redstone lamp*.") and *Explanation* (e.g., *"Because there's ground, and also a star wouldn't be made out of lava."*). These connections highlight a distinction in how students with different levels of situational interest approach interview dialogues: high-SI students tended to produce succinct, emotionally expressive remarks during gameplay interviews, whereas low-SI students preferred engaging in more elaborative yet affectively neutral responses.

In detail, the ENA model of the high-SI student group showed stronger co-occurrence between *Brief Response* and all five question types (Fig. 1, *left*). While it is perhaps less surprising to see stronger connections between *Closed-ended* questions and *Brief r*esponses, given that such questions typically elicit binary or concise answers (e.g., yes or no), it is worth noting that, even questions intended to encourage elaboration may be associated with brief replies from highly engaged players in some cases (e.g., *Open-ended, Process*). This response pattern may be due to high-SI students' heightened focus on the gameplay, which led them to prioritize completing the task at hand over providing detailed responses to the interviewer's prompts. For instance, when

an interviewer asked a high-SI student an *Open-ended* question: *"So, I know you're having a great time here. Is there anything about this world that you find extra, extra, extra exciting?"* The student replied simply, *"The mods,"* without offering any further description. When the interviewer followed up with *"Can you tell me any of them?"* the student had already shifted attention to an unfolding in-game event (e.g., *"MCS eagle! Who? Why is this ..."*). Thus, instead of continuing the conversation, the student began narrating aloud what was happening in the game.

In addition, we observed that *Enthusiastic* responses were also linked to all five question types among high-SI students. These connections suggest high-SI students often responded to questions with expressions charged with strong excitement or passion during interviews. For instance, when asked about their favorite thing in space, one high-SI student answered excitedly, *"Space! It's just so fascinating. I, I...Probably, my favorite thing is probably the black hole."* Many of these moments coincided with successful in-game actions or milestone completions, including one where a high-SI student cheerfully announced, *"Yay, we did it!"* after building a base in the middle of a crater. Beyond marking success, these enthusiastic responses also appeared in moments of discovery or sense-making while immersed in game activities. For example, when the interviewer pointed out a model of a 3D printer in-game, the student responded with *"That's what this is, cool!"* Further, enthusiasm was expressed in appreciation for gameplay features, as seen in one student's joyful reaction, *"Woo, woo. I'm using the port."* Taken together, these positive responses highlight high-SI students' immersive enjoyment and emotionally rich engagement with the in-game explorations.

Compared to their peers in the high-SI group, the low-SI group had weaker connections to *Brief Responses*. Instead, the ENA model (Fig. 2) revealed stronger connections between *Explanation* and *Process* (lw=-0.03), *Open-ended* (lw=-0.06), *Follow-up* (lw=-0.03), and *Neutral* (lw=-0.05). These explanatory patterns suggest that low-SI students tended to offer longer and more detailed responses during the interview. The additional detail and explanation made their thinking processes more explicit in some cases, particularly when students paused gameplay to focus on their responses. For example, when being asked an *Open-end* question: *"Okay. What does the airlock do?"*, a low-SI student offered a longer explanation that reflected their level of subject knowledge: *"Uh, it helps, like, keep the atmosphere inside of our base, like, safe, breathable, and not bring anything that could harm humans inside."* Similarly, when being prompted to describe their decision, *"So what made you decide to do temperature measurement at that, in that spot?"* The low-SI student would share the reasoning behind their action: *"Because I was kind of curious about how cold it was."* These responses indicate that low-SI students tend to articulate their thought processes in greater detail and participate more actively in dialogue with the interviewer.

Yet, while the responses of low-SI students were explanatory in nature, they were sometimes marked by hesitancy or uncertainty, featuring hedging phrases such as *"I guess"*, *"Maybe?"*, or were delivered with a questioning tone that suggested a lack of confidence. For example, when the interviewer asked a low-SI student to describe their in-game intentions: *"What will you do with the spacesuit, once you find it?"* The student had not yet come up with a plan: *"I ... Well, actually, I don't know. Because I guess we could just, um, use drones maybe, and rovers."* When experiencing these moments of

uncertainty, low-SI students sometimes used interactions with the interviewer as an opportunity to clarify their thinking and engaged in a process of reasoning aloud throughout the dialogue. In other words, rather than withholding incomplete thoughts, they seemed more likely to verbalize tentative ideas, and work through their understanding as part of their ongoing sense-making process. For instance, when the interviewer asked a student from the low-SI group, *"Alright, while we wait, what's your plan now?"* A low-SI student initially shared their lack of plan: *"I don't know."* Then, instead of pausing the conversation, the student continued thinking-aloud: *"Um…We still need like the, the health place. And ... But I don't know. It could be like, here."* As the conversation progressed, the student began to make sense of their intentions in real-time: *"Yeah. And then…I was thinking just one."* This pattern suggests that low-SI students sometimes utilize the explanatory process during an interview as an opportunity to work through uncertainty surrounding their gameplay actions and choices. Similar patterns have been seen for metacognitive reasoning during this type of interview within other learning environments as well ([4]).

It is worth noting, however, that qualitative review also revealed moments of uncertainty expressed by high-SI students during play. In such cases, instead of explaining their thought process to the interviewer, they tended to offer brief yet direct responses that explicitly acknowledged their lack of understanding (e.g., *"I don't know"*), before promptly redirecting their attention back to the game to figure things out.

4.2 Potential Impacts of Interviewer Strategy

To examine whether the differences in interview response between high- and low-SI students were driven by interviewer behavior, we employed ONA to assess whether there were any variations in how interviewers structured their questions and interacted with students across the two groups. Along the X axis, a Mann-Whitney test (U=3.00, p=0.11, r=0.70 at alpha=0.05) showed no statistically significant differences in interviewer engagement. This result demonstrates that interviewers maintained a consistent interaction pattern across two groups, engaging high- and low-SI students with similar interview structures. This finding further suggests that the observed differences in student interview patterns are not likely driven by interviewer variability but instead reflect meaningful differences in how students with varying levels of interest participated in the interviews during gameplay. It is also worth noting that the interest survey was administered on the fourth day of the camp and was not analyzed until the camp concluded. Thus, interviewers were not aware of student situational interest levels at the time of the interviews. In sum, the ONA results shown here aim to rule out differences in interviewer engagement; in-depth interpretation will be shared in upcoming work.

5 Discussion and Limitations

In this study, we examined how students with varying levels of situational interest (SI) differ in their interview behaviors. We used ENA to compare interview patterns between high- and low-SI students, and ONA to confirm that the observed patterns were

not driven by the way interviewers guided the conversation. Together, our results suggest that during real-time interviews alongside WHIMC, high-SI students tended to offer brief yet enthusiastic responses. We believe that these interview patterns, rather than signaling disinterest or disengagement, reflect high-SI students' deep gameplay immersion, prioritizing their attention toward the task at hand over extended dialogue. Thus, once they feel their ideas have been clearly communicated and understood, they prefer to remain absorbed in the game rather than being diverted from their goals.

In contrast, low-SI students were more open to engaging in conversations with the interviewer, even if it meant briefly shifting focus away from the gameplay. They tended to be more verbally expressive during interviews, often offering explanatory yet emotionally neutral responses. Even during moments of uncertainty, rather than withdrawing from the conversation, low-SI students were more likely to use the interaction with the interviewer as an opportunity to make sense of their actions, clarify their thinking, or formulate a plan in real-time. In many cases, the interviewers' questions acted as reflective prompts, encouraging low-SI students to think-aloud and gradually construct their reasoning as the dialogue unfolded. This pattern, also seen for metacognitive reasoning in another learning environment [4], highlights how well-timed, structured questioning can support students with initially lower interest in reflecting more deeply on their gameplay experiences and producing more task-relevant explanations. These findings also align with prior research demonstrating that situational interest can be intentionally fostered through thoughtful prompts and instructional strategies [25], sup porting the development of deeper engagement and emerging individual interest [9].

These findings further suggest that interest levels shape not only what students say during gameplay interviews, but also how and why they engage with the interviewer. Real-time interview responses appear to reflect distinct motivational orientations: high-SI students prioritize staying immersed in the game and may offer concise but affectively rich responses to avoid disrupting that immersion, whereas low-SI students use the interview as a space for reflection and sensemaking. This suggests that interviews can serve different purposes depending on students' current interest states. Although more detailed responses might aid researchers' understanding of learning phenomena, these findings highlight the value of interpreting student discourse in context and tuning interview strategies to students' motivation and engagement. As such, it is important to use different interviewer prompts for immersive learners compared to exploratory reasoners. This is key to the effective use of Data Driven Classroom Interviews (DDCIs; [2,10]), which are intended to capture students' reasoning as it unfolds. Our study demonstrates how these interviews, when deployed during gameplay, can elicit expressions of affective and cognitive engagement that may not surface in post-hoc reflection.

While our analysis offers insights into how students' interest shapes their interview behaviors during gameplay, we acknowledge several limitations. First, we recognize that the small sample size may limit the generalizability of our findings. Second, the current codebook includes a relatively narrow range of question and response types, potentially constraining the diversity of interaction patterns observed. Future research could expand the sample size and set of codes—covering both interviewer questions and student responses—to better represent the range of interview dynamics. Themes related to uncertainty might lend further insights into gameplay patterns identified

through a qualitative review of interview data. In addition, future work could also integrate within-system interaction behaviors such as gameplay milestones into the analysis, which may help align in-game context with student discourse, offering a more nuanced understanding of how students' interests fluctuate in response to in-game events.

In summary, this study adds to the ongoing discussion on how situational interest manifests and shapes various dimensions of students' learning, such as engagement [25], the development of individual interest [1] and their in-game observations [28]. By examining students' interview patterns during real-time gameplay, we extend prior work by illustrating students with high and low interest levels engage differently in the interview dialogue, revealing variations both in students' emotional engagement, and in how they make sense and reflect on their in-game experiences. We hope these findings could further inform more responsive interview strategies that better align with students' interest levels and help foster deeper engagement during gameplay.

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