Investigation of the Characteristics of Successful and Less Successful Students in Guided Simulation-Based Inquiry Learning in Physics Education

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Here we are, once again… I have always found this part challenging to write since it is difficult to arrange everything I have experienced into a structured flow. Therefore, I believe it is better to write whatever comes to my mind and go with the flow, rather than following the structured approach I used throughout the entire thesis. It is still so hard to believe that it has been a year since I embarked on this journey and finished everything within this period.

I wrote this sentence exactly 2 years ago while writing the acknowledgment part of my first master's thesis: "Life is so unpredictable that we can find ourselves either in the darkest edge of the mind or in the places where we need to be.". I also mentioned in this part that it was the most challenging part of my life, not realizing that each subsequent step would be even more difficult than the last. However, in this chapter of my life, I would say I have always felt like I was exactly where I needed to be despite the numerous challenges and obstacles. I know it would have been impossible without believing in myself and encountering so many amazing people along the way. Therefore, I would love to thank everyone whom I have come across throughout the latest most challenging but fulfilling part of my life.

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CONTENTS

Abstract

Introduction: Inquiry-based learning (IBL) is a constructive approach that supports learning processes through questioning, researching, experimenting, and concluding. With the integration of modern technology, guided simulation-based inquiry learning environments are used to enhance traditional science education. Despite its well-known advantages, the effectiveness of such environments is dependent on a variety of factors, including prior knowledge, metacognition and self-regulation. Therefore, in this exploratory study, the aim was to determine the characteristics of successful and less successful students in guided simulation-based inquiry learning within Physics education by exploring the cumulative effects of these factors and identifying distinct student profiles based on their characteristics.

Method: The study used a quasi-experimental, exploratory research design with pre-test and post-test measures. Thirty bachelor and pre-master students from different departments at the University of Twente were recruited. The learning environment, developed using the Go-Lab platform and focusing on series and parallel electric circuits, was utilized in addition to the measurements of prior knowledge, metacognition, self-regulation, and learning performance.

Results: The study revealed that both prior knowledge and organizational skills, as a part of self-regulation, were significant predictors of learning outcomes. There were four profiles of students identified by the cluster analysis: two for successful students and two for less successful students. Cluster 1 in successful students relied more on prior knowledge, whereas Cluster 2 demonstrated strong metacognitive and self-regulation skills. Cluster 1 in less successful students had stronger metacognitive and self-regulation skills but lacked sufficient prior knowledge, while Cluster 2 exhibited deficiencies across all domains.

Conclusion: This study contributes to understanding how the cumulative effects of prior knowledge, metacognition, and self-regulation play a role in learning outcomes in guided simulation-based inquiry learning, underscoring the need for personalized instructional strategies that enable students to reach their full potential.

Keywords: guided simulation-based inquiry learning, prior knowledge, metacognition, self-regulation, learning outcomes

CHAPTER 1

Introduction

In the past several years, there has been a growing interest in inquiry-based learning (IBL) in different areas, such as science, math, and social studies (Harlen, 2013; Pedaste et al., 2015; Shih et al., 2010). IBL is defined as a general process through which individuals discover new relationships, develop hypotheses and test them by conducting experiments (Pedaste et al., 2012). It is an approach used particularly for teaching and learning through various actions, such as questioning, observing, researching, analyzing, and assessing various situations, by providing students with authentic scientific problem (Donnely et al., 2014). Furthermore, with the advancement of modern technology, IBL can be implemented into computer simulations to improve learning outcomes in traditional science education, which is called a simulation-based inquiry learning environment (Rutten et al., 2015).

Simulations are considered crucial for inquiry learning since they provide essential interactive content for the engagement of students in the learning environment (Olde et al., 2013). Specifically, simulations, which replicate tasks within scenarios, have been found to improve traditional science education (Rutten et al., 2015; Sagir & Bello, 2021; Smetana & Bell, 2012). Nonetheless, while simulation-based inquiry learning offers potential benefits, it has been argued that its effectiveness depends on the guidance provided (Olde et al., 2013). Regarding this, providing sufficient guidance, such as in formulating hypotheses and conducting experiments, allows students to actively engage in the scientific inquiry process (Lehrer & Schauble, 2012; van Joolingen et al., 2007; Rutten et al., 2012). Therefore, it is generally agreed that the inquiry process must be scaffolded for simulation-based inquiry to be effective (Olde et al., 2013). However, there are different opinions on the type of guidance that is most effective: some advocate for the benefits of unguided/minimally guided learning environments (Furtak et al., 2012) whereas others claim that strongly guided learning environments are more effective Moreno (2004). Concerning this debate, it has been argued that several factors, such as prior knowledge and inquiry experience, influence the effectiveness of the guidance provided (Sun et al., 2022).

In addition, learning performance in simulation-based inquiry learning environments can be influenced by individual factors, just as in any learning environment (Sun et al., 2022). Previous studies have investigated various individual factors that affect students' inquiry learning performance, notably prior knowledge (van Riesen et al., 2018), metacognition (Abdelrahman, 2020), and self-regulation (Lai et al., 2018). For instance, in a simulation-based learning environment, prior knowledge plays a critical role by allowing students to pass initial exploratory experiments and directly start formulating and testing hypotheses; thus, facilitating understanding of a particular phenomenon under study (Mulder et al., 2015). Furthermore, metacognition is considered as crucial for guiding the inquiry process in science learning (Seraphin et al., 2012), and Ucar and Sungur (2017) emphasizes that self-regulation is essential for students to effectively manage their actions and draw conclusions throughout science inquiry activities.

It is crucial to recognize that individual factors such as prior knowledge, metacognition, and self-regulation do not influence learning performance in isolation. Instead, these factors interact in complex ways that can significantly impact a student's ability to succeed in educational environments. For instance, research has shown that there are relationships between prior knowledge and metacognition (Hosein & Harle, 2018), prior knowledge and self-regulation (Mihalca, 2018), and self-regulation and metacognition (Arslan, 2014). These interactions suggest that a comprehensive understanding of learning performance must consider how these factors interplay.

Despite these insights, most studies have primarily concentrated on examining the individual effects of these factors on learning outcomes, highlighting a significant gap in the literature. To date, no research has investigated the interactions between these key individual factors and learning performance, especially within guided simulation-based learning environments. A comprehensive exploration of this dynamic would enable a comparison of various relationships in terms of their direction and strength. Moreover, there has been a lack of research into profiling students who are successful or less successful in guided simulation-based inquiry learning, taking into account the interplay among these critical influencing factors. Adopting this cumulative approach is crucial, as understanding the unique traits of each student is key in IBL (Burden & Byrd, 2010).

The current study aims to address the aforementioned gap in the literature by exploring the cumulative effect of three interconnected factors—prior knowledge, metacognition, and self-regulation—on students' learning performance in physics within a guided simulation-based inquiry learning environment. Additionally, it aims to identify the characteristics of successful and less successful students in such environments, helping to understand why some students perform better in science tasks and suggesting ways to help every student better understand and succeed in science inquiry.

Theoretical Framework

1.1. IBL and Science Learning

Science education scholars who adopt a constructivist philosophical stance recognize that students possess prior knowledge of the physical world before engaging in formal classroom instruction (Srisawasdi & Panjaburee, 2015). Such prior knowledge often includes incomplete conceptual understandings, known as misconceptions, which contradict accepted scientific knowledge (Srisawasdi & Panjaburee, 2015; Westbrook & Marek, 1991). These misconceptions have been shown to be pervasive and resistant to change through traditional educational methods (Üce & Ceyhan, 2019). Addressing these misconceptions requires learning environments that are supported by constructivist processes of knowledge acquisition (Kayali & Tarhan, 2004). This approach enables learners to actively engage cognitively as they explore new principles and explanations of specific topics, rather than relying solely on direct instruction (Srisawasdi & Panjaburee, 2015).

One of the primary approaches to developing such learning environments in science education is IBL. This approach not only actively engages students and enhances their enthusiasm for science (Olde et al., 2013) but also addresses misconceptions by challenging students with their erroneous assumptions during experiments, thereby encouraging them to revise their understanding (Siantuba et al., 2023). Defined as an approach that leverages students' existing knowledge, attitudes, and skills, IBL enables them to formulate hypotheses, conduct experiments, and interpret data (Nasution, 2018). Its unique practices, such as visualizing abstract concepts and integrating multiple representations, foster deeper conceptual understanding (Olympiou et al., 2013). Furthermore, IBL promotes active participation in knowledge acquisition through a self-directed scientific exploration process (de Jong & van Joolingen, 1998; Pedaste et al., 2015). This approach enables students to consider how to think and act scientifically rather than memorizing information in science education as emphasized in John Dewey's educational philosophy (Johnston, 2013; Sun et al., 2022). Ultimately, IBL aims not just to let students explore and experiment within a subject area (de Jong, 2006), but also to enhance their scientific literacy by engaging them in higher-level thinking activities (Orcutt, 1997).

To achieve the aforementioned goals, an IBL environment should include five general phases, as identified by Pedaste et al. (2015): *orientation*, *conceptualization*, *investigation*, *conclusion*, and *discussion* (see Table 1 for an overview). The orientation phase ignites students' interest and provides general information about the learning problem. The conceptualization phase encompasses two sub-phases: questioning, where research questions are developed based on the learning problem, and hypothesis generation, where hypotheses related to these questions are formulated. The investigation phase consists of three sub-phases focusing on actions to answer the research questions and test the hypotheses: exploration (e.g., systematic planning for data collection), experimentation (e.g., designing and conducting experiments), and data interpretation (e.g., synthesizing new knowledge from the results). In the conclusion phase, implications are drawn from the data gathered to answer the research questions and test the hypotheses. Finally, in the discussion phase, learners present their findings to one another, collect feedback, and reflect on all the implications they have made throughout the learning process.

Table 1

Pedaste et al. (2015)'s Five General Inquiry Phases

Orientation Phase	Conceptualization Phase	Investigation Phase	Conclusion Phase	Discussion Phase
Ignites students' interest	*Questioning:* Developing research questions based on the learning problem	*Exploration:* Systematic planning for data collection to answer research questions and hypotheses	Drawing implications from the gathered data to answer research questions and hypotheses	Presenting findings to each other
Provides overall information about the learning problem	*Hypothesis Generation:* Generating hypotheses regarding the research questions	*Experimentation:* Designing and conducting experiments		Collecting feedback
		Data Interpretation: Synthesizing new knowledge obtained from experiments		Reflecting on the implications made throughout the learning process

1.2. Simulation-Based Inquiry Learning

An IBL approach requires students to actively participate in hands-on activities and experimentation process (Kapici et al., 2022; Putri et al., 2021). However, due to various reasons, such as the lack of necessary physical lab equipment or the potential dangers and risks involved, it is not always feasible to conduct these activities (Usman, 2021). Regarding this, modern technology in education offers students numerous opportunities for inquiry. One of these technology-based environments is simulations, defined as artificial representations of real or virtual world (Richards & Szilas, 2012). According to Eysink et al. (2009), technology-based environments, such as simulations, are well-suited for integration into IBL settings. These environments provide a process model that enables students to test hypotheses by manipulating independent variables and observing the resulting changes. The main purpose of this investigation-based learning is to enable students to develop domain knowledge and proficiency in scientific inquiry (Gobert & Pullant, 2004). Moreover, simulations allow students to conduct experiments and visualize abstract features, making these features more observable and visible and this allows students to acquire deeper and transferable knowledge (Ainsworth & VanLabeke, 2004; Rutten et al., 2012). Therefore, it can be stated these visualizations promote the integration of new knowledge with existing understanding, a critical aspect from the constructivist perspective (Cook, 2006). Furthermore, Huang et al. (2016) states that simulation-based inquiry learning environments offer numerous characteristics, such as interactive features and real-life scenarios, that are beneficial for facilitating conceptual change (also see Moore et al., 2014). This is also supported by Srisawasdi and Sornkhatha (2014)'s findings, which indicate the effects of using simulations in IBL on students' conceptual learning. Similarly, several studies have demonstrated that using simulations in inquiry learning environments effectively enhances students' understanding of conceptual science facts (e.g., Srisawasdi & Kroothkeaw, 2014; Trundle & Bell, 2010; Olympiou et al., 2013). Therefore, simulations can significantly facilitate learning when integrated into IBL.

When compared to hands-on inquiry learning, simulation-based inquiry learning offers students the advantage of benefiting from an inquiry environment without any harm by facilitating the process of knowledge acquisition (de Jong, 2006; Olympiou et al., 2013, van Joolingen et al., 2007). When considering the nature of scientific content, it is essential to implement technology and appropriate instructional methods in science education (Srisawasdi & Panjaburee, 2015). Thus, simulation-based inquiry learning is considered a promising approach for science educators to enhance students' mental interaction with the physical and social world, facilitating their understanding and communication of scientific ideas (Srisawasdi & Panjaburee, 2015). Studies have demonstrated that simulation-based inquiry learning functions as a facilitator by transforming the alternative conceptions held by learners (Bell & Trundle, 2008; Srisawasdi & Kroothkeaw, 2014), fostering the acquisition of domain-specific knowledge rather than formalized knowledge (Suits & Srisawasdi, 2013; Veermans et al., 2006), enabling students to focus more theoretical and coherent understanding of scientific concepts (Winber & Berg, 2007), fostering a positive attitude towards science learning (Pinatuwong & Srisawasdi, 2014), and addressing misconceptions in a science domain (Siantuba et al., 2023; Srisawasdi & Panjaburee, 2015). Based on these, previous studies indicated that simulations integrated in IBL could improve conventional science education (Rutten et al., 2015; Smetana & Bell, 2012). Regarding this, Chou et al. (2022) revealed that students who received IBL with simulation in physics education performed better than those without simulation. This is also compatible with the shared belief in science education that students should actively participate in inquiry, experiments, and discovery while also improving their science-related skills (Lehtinen & Viiri, 2016). Some examples of such learning environments include Inquiry Island (White et al., 2015); Co-Lab (van Joolingen et al., 2003), Web-based Inquiry Science Environment (Slotta, 2013); and Go-Lab (de Jong et al., 2021).

1.3. Guidance for Simulation-Based Inquiry Learning

Simulation-based inquiry learning environments have been proven effective many times (see Chou et al., 2022; de Jong, 2006; Srisawasdi & Sornkhatha, 2014). However, their impact on learning performance cannot be guaranteed by the environment alone. Instead, it depends on students' inquiry skills to complete scientific investigations, which are often found to be lacking (Arnold et al., 2014; Edelson et al., 1999). In addressing this, Smetana and Bell (2012) claim that simulations are effective tools for IBL when they are supported with the different kind of instructions and exceptional guidance for learners to follow the various steps of IBL. With proper guidance, students can effectively learn about science and actively participate in scientific inquiry. This includes following the established steps used by researchers, such as formulating hypotheses, collecting evidence, designing experiments, and assessing hypotheses based on the evidence (Lehrer & Schauble, 2012; van Joolingen et al., 2007; Rutten et al., 2012). Thus, it is widely accepted that for simulation-based inquiry learning to be effective, the inquiry process should provide a scaffolded environment (Olde et al., 2013), which has also been supported by several review studies (e.g., Lazonder et al., 2016; Rutten et al., 2012; Smetana & Bell, 2012).

When considering the types of guidance implemented in a learning environment, various forms are available, such as “scaffolding” and “direct representation of information” (Lazonder & Harmsen, 2016; Sun et al., 2022). Scaffolding is a type of guidance that assists students in performing demanding tasks by providing appropriate tools or examples to facilitate the learning process, and it can be gradually removed or faded as learners become more proficient (Lazonder & Harmsen, 2016). In a simulation-based learning environment, this can be achieved by offering visual aids (Homer & Plass, 2014), personalized support (Ibanez et al., 2016), or specific tools for conducting experiments (van Riesen et al., 2022) and formulating testable hypotheses (Kuang et al., 2019). Scaffolding can typically support the inquiry process throughout the entire learning experience, depending on the nature of the environment (Sun et al., 2022).

Direct representation of information enables learners to access relevant details necessary for a particular task (Sun et al., 2022). This can be provided through various formats such as forms, instructions with pictures, narrative information (Liu & Chuang, 2011), and presentations (Petersen et al., 2020). In the context of inquiry, direct representation of information can be introduced during the orientation phase (Brophy et al., 2013), throughout the inquiry process (Liu & Chuang, 2011), or in specific phases (Petersen, 2020). Previous studies have shown that this type of guidance significantly enhances students' learning performance by reducing the cognitive load of the inquiry process (Brophy et al., 2013; Petersen, 2020).

In addition to the type of guidance, the amount of guidance is also critical for its effectiveness. Some argue that minimally guided environments, where students imitate problem-solving activities of experts, are more effective in fostering exploration (Furtak et al., 2012). However, others highlight the risks of confusion and misconceptions (Brown & Campione, 1994). On the contrary, Moreno (2004) asserts that strongly guided learning environments are more beneficial and efficient than unguided or minimally guided ones. Regarding this debate, Sun et al. (2022) concluded that the effectiveness of any type of guidance (e.g., scaffolding or direct representation of information) and determining the appropriate amount of guidance depend on learner factors such as prior knowledge and existing inquiry strategies. This assertion is supported by Brenner et al. (2017), who found that students with low prior knowledge benefit from more guidance. Similarly, van Riesen et al. (2018) argued that students need some level of prior knowledge to derive benefits from guidance in inquiry learning. Therefore, it can be argued that prior knowledge is a critical learner characteristic, especially in a guided simulation-based inquiry learning environment.

1.4. Prior Knowledge and Guided Simulation-Based Inquiry Learning

According to the constructivist approach to learning, understanding students' experiences and prior knowledge is considered fundamental for developing new learning (Bransford et al., 2001). For instance, students with high prior knowledge can acquire new skills more easily than those with low prior knowledge, whose attention might be overwhelmed by new information (Winters & Azevedo, 2005). This is because prior knowledge facilitates memory processing by providing a structure for integrating new information (Shing & Brod, 2016). Therefore, understanding the role of prior knowledge in IBL is crucial because learners with more knowledge can better connect new information to their existing knowledge (Braasch & Goldman, 2010).

In simulation-based inquiry learning, many students struggle to devise effective experiments due to a lack of prior knowledge of experimental design, often resulting in experiments that are irrelevant to their research questions and hindering their ability to draw conclusions (de Jong, 2006b). Consequently, prior knowledge becomes a critical factor, as it not only affects the design and relevance of experiments; but also, influences motivational factors such as learners' self-concept (Richter et al., 2022). Moreover, the alignment between prior knowledge and the learning environment significantly influences learning outcomes (Hewson, 2004). This is corroborated by Wang et al.'s (2010) study, indicating that students with moderate to high prior science knowledge significantly outperform those with low prior science knowledge in learning environments employing inquiry-based instruction.

Prior knowledge is also crucial in determining the appropriate amount of guidance in IBL. Students with low prior knowledge participating in IBL tend to use less sophisticated strategies and require more attempts to reach conclusions (van Riesen et al., 2018).

Additionally, Zacharia et al. (2015) noted that students need sufficient prior knowledge of the subject domain to effectively engage in the learning environment. Therefore, it follows naturally that, according to the "expertise reversal effect" (Kalyuga, 2007), students with little prior knowledge benefit from assistance, while students with higher prior knowledge benefit from minimal assistance. In this regard, although Brenner et al.'s (2017) findings in two of the five clusters support the expertise reversal effect in the context of IBL, they also found in two other clusters that students with low prior knowledge benefited from lower amounts of guidance. This finding is further supported by Chernikova et al.'s (2020) meta-analysis, which demonstrates that students with higher levels of prior knowledge benefit more from the guidance (e.g., worked examples) provided in IBL. Therefore, it can be argued that prior knowledge may not be the sole factor in determining the appropriate amount of guidance and predicting learning performance; other factors such as metacognition and self-regulation might also play significant roles, as claimed in Brenner et al.'s (2017) study.

1.5. Metacognition and Guided Simulation-Based Inquiry Learning

Metacognition is defined as the experiences that each individual has about their own cognitive and mental processes, enabling us to monitor, control, and optimize our actions (Flavell, 1979; 2004; Nelson & Naren, 1990). Thus, metacognition involves understanding the mechanisms of knowledge acquisition, including what we know about our cognitive processes and how we will use them to learn and remember (Cera et al., 2013; Ormrod, 2004). Researchers further conceptualize metacognition by dividing it into two interrelated subcomponents, metacognitive knowledge and metacognitive regulation (Brown, 1987; Flavell 1987).

Metacognitive knowledge refers to an understanding of our own cognitive processes. Schraw and Moshman (1995) identified three subcomponents of metacognitive knowledge: declarative, procedural, and conditional knowledge. Declarative knowledge encompasses our awareness of how we learn and what affects our learning. Procedural knowledge involves knowing the strategies and methods that enhance our learning performance. Conditional knowledge includes understanding when and how to apply different cognitive strategies. Altogether, this knowledge covers our insights into how we learn, the strategies that work best for us, and the optimal conditions for various cognitive activities (Schraw and Moshman, 1995).

Metacognitive regulation, on the other hand, is referred as the specific activities we engage in to enhance learning and memory (Schraw & Moshman, 1995). It comprises three key sub-activities: planning, monitoring, and evaluating (Jacobs & Paris, 1987; Veenman et al., 2006). Planning entails organizing a cognitive task by choosing suitable strategies and resources. Monitoring involves being aware of our progress and assessing our performance during the task. Evaluating encompasses reviewing the outcome to see if it meets our learning goals and if the strategies used were effective (Schraw & Moshman, 1995).

Considering all these aspects, it has been claimed that these metacognitive skills play an important role in setting learning goals, managing tasks, and applying strategies effectively to better coordinate study progress (Cera et al., 2013). In other words, if students are aware of their metacognitive skills, they will thrive academically (Young & Fry, 2008). This awareness of one's own cognitive processes and strategies is referred to as metacognitive awareness. Defined as the process of employing reflective thinking to build an understanding of one's personal knowledge, task comprehension, and strategy awareness within a specific situation, metacognitive awareness enables students to apply their metacognitive skills effectively, leading to improved academic performance (Ridley et al., 1992).

Previous studies indicate that higher metacognitive awareness is positively correlated with high academic achievement (see Abdelrahman, 2020; Young & Fry, 2008). Furthermore, it has been shown that metacognitively aware students are more strategic and perform better than unaware ones (Pressley & Ghatala, 1990). This is because metacognitive awareness enables students to plan, control and monitor their progress in a way that directly enhances learning performance (Schraw & Dennison, 1994). Although the relationship between metacognitive awareness and learning performance in guided simulation-based inquiry learning is not explicitly addressed, it is acknowledged that metacognition plays a crucial role in science learning within an inquiry-based environment, serving as a guide throughout the thinking process of inquiry (Seraphin et al., 2012). This is also supported by the fact that IBL is associated with improving learners' metacognitive abilities, which is linked to self-regulation (Shraw et al., 2006).

1.6. Self-regulation and Guided Simulation-Based Inquiry Learning

Self-regulation is defined as one's ability to actively engage in the learning process, incorporating aspects of metacognition and motivation (Zimmerman, 1989). According to Zimmerman (2000), self-regulated learners are defined as "those who are proactive in their efforts to learn since they are aware of their strengths and limitations and because personally set goals and task-related strategies guide them". Wolters (2003) further defines self-regulated students as self-reflective learners but also those who have cognitive and metacognitive skills to understand, monitor, and manage their learning processes. Hence, one of the main purposes of education in the 21st century is to prepare students to become independent learners with high self-regulatory skills. Based on these, self-regulation involves the learner's initiating action, setting goals, and managing their efforts to achieve desired outcomes. This includes self-monitoring and self-evaluation (metacognition), time management, goal setting, seeking assistance, organization skills and the management of physical and social environments (Magno, 2010; Zimmerman & Risemberg, 1997). Furthermore, Ridley et al. (1992) point out that self-regulation can be seen as an interactive and multifaceted process of three primary dimensions: 1) development of metacognitive awareness of self and others; 2) clarifying and utilizing goals in light of that awareness; and 3) applying and monitoring actions.

Several research findings suggest that students with higher self-regulation skills are more successful in learning compared to those with lower skills (see Barnard-Brak et al., 2010; Demirel & Turan, 2010; Kırmızı, 2015). In Cheng et al.'s (2011) study, it was demonstrated that self-regulatory skills, including students' learning motivation, goal setting, action control, and learning strategies, significantly contribute to learning performance. Moreover, the quality of IBL is influenced by self-regulated activities, as IBL requires students to regulate their learning processes (Pedaste et al., 2012). This finding is supported by Lai et al.'s (2018) study, which found that students with higher self-regulation achieved more in self-regulated science inquiry environments. It has been argued that students with low self-regulatory skills may acquire less knowledge or struggle to engage in inquiry-based science activities (Liu et al., 2014; Rahimi et al., 2015). This argument is further supported by Ucar and Sungur's study (2017), which illustrates that students need to be self-regulated throughout science inquiry activities to control their actions and draw informed conclusions. Given these considerations, although the relationship between self-regulation and guided simulation-based inquiry learning has not been explicitly mentioned, it might be speculated that individuals with higher self-regulation skills might benefit from minimal guidance, whereas those with lower self-regulation skills may require more extensive support to engage in the learning process.

1.7. Intercorrelations Between Various Individual Factors

As previously mentioned, students' characteristics, such as prior knowledge, metacognition, and self-regulation might influence learning performance (Abdelrahman, 2020; Demirel & Turan; 2010; Wang et al., 2010). Kostons and van der Werf (2015) claimed that for students to activate their prior knowledge efficiently, they need sufficient metacognitive knowledge because metacognitive processing includes deciding on how, when, and why to use learning strategies, such as activating prior knowledge (Schwar & Dennison, 1994). The study supports this relationship between prior knowledge and metacognition, demonstrating that students with prior knowledge are better at metacognitive evaluation than students with middle and low prior knowledge (Nietfeld & Schraw, 2002). Similarly, Mihalca (2018) and Ericsson (2006) denote that the ability to monitor one's performance, which is crucial for self-regulation, relies on students' ability to use cues that are predictive of learning performance, such as prior knowledge. Lastly, self-regulation and metacognition are positively correlated; that is, students with higher levels of self-regulation are predicted to have higher metacognitive skills (Arslan, 2014; Çiftçi, 2012).

While these factors have been extensively shown to directly affect learning performance in various forms of IBL environments, their cumulative effects have yet to be explored, especially in a guided simulation-based inquiry learning environment. Some research findings indicate that they do not affect learning performance in isolation (e.g., Brenner et al., 2017; Cera et al., 2013). Instead, they may interact with each other when exerting their effects. Therefore, the overall impact of these factors is deemed significant due to their interconnected relationships. Given all these results, in conclusion, the answers to the following questions will be explored to investigate the impacts of prior knowledge, self-regulation, and metacognition on learning outcomes in guided simulation-based inquiry learning.

1.8. Research Questions

In this study, the aim is to determine the characteristics of successful and less successful students in guided simulation-based inquiry learning in Physics education. It is important to specify these characteristics since it has been known that students' characteristics, such as prior knowledge, metacognition, and self-regulation, might have a cumulative or individual impact on learning performance. To that end, the questions below will be examined within the scope of this study:

1. What is the relative contribution of prior knowledge, metacognition, and self-regulation to predicting learning outcomes in a guided simulation-based inquiry learning environment?
2. What are the distinct profiles of successful and less successful students in guided simulation-based inquiry learning, based on variations in their levels of prior knowledge, metacognition, and self-regulation?

1.9. Scientific & Practical Relevance

IBL has been extensively explored as an approach to foster science learning across various educational levels. However, it remains unclear which group of students might benefit the most from these environments. Moreover, it is even more uncertain who might benefit from guidance in such environments and who might not. The results of this study could provide richer insights into this dilemma, potentially guiding educators in tailoring learning experiences more effectively to meet diverse student needs. Thus, with these insights, teachers will be able to identify why certain students are good at science activities and determine strategies to assist students in improving their understanding and performance in scientific inquiry and to create individualized learning plans.

CHAPTER 2

Method

2.1. Research Design

This study employs a quasi-experimental, exploratory research design with pre-test and post-test measures to identify profiles of successful and less successful students in guided simulation-based inquiry learning, based on variations in their levels of prior knowledge, metacognition, and self-regulation. Given the exploratory nature of this study and the small sample size, the focus is on in-depth analysis rather than generalizability.

2.2. Participants

The current study was conducted with 30 (19 males and 11 females) bachelor and pre-master students from different departments at the University of Twente, with a mean age of 20.60 (*SD* = 3.56). Detailed characteristics of the participants are presented in Table 2.

Table 2

Frequency Analysis of Faculty and Gender Distribution

Faculties	Male		Female	
	N	%	*N*	%
Behavioral and Management Science	10	33.33	8	26.67
Engineering Technology	3	10	3	10
Technical Natural Sciences	3	10	0	0
EEMCS*	3	10	0	0
Total	19	63.33	11	36.67

*EEMCS: Electrical Engineering Mathematics and Computer Science

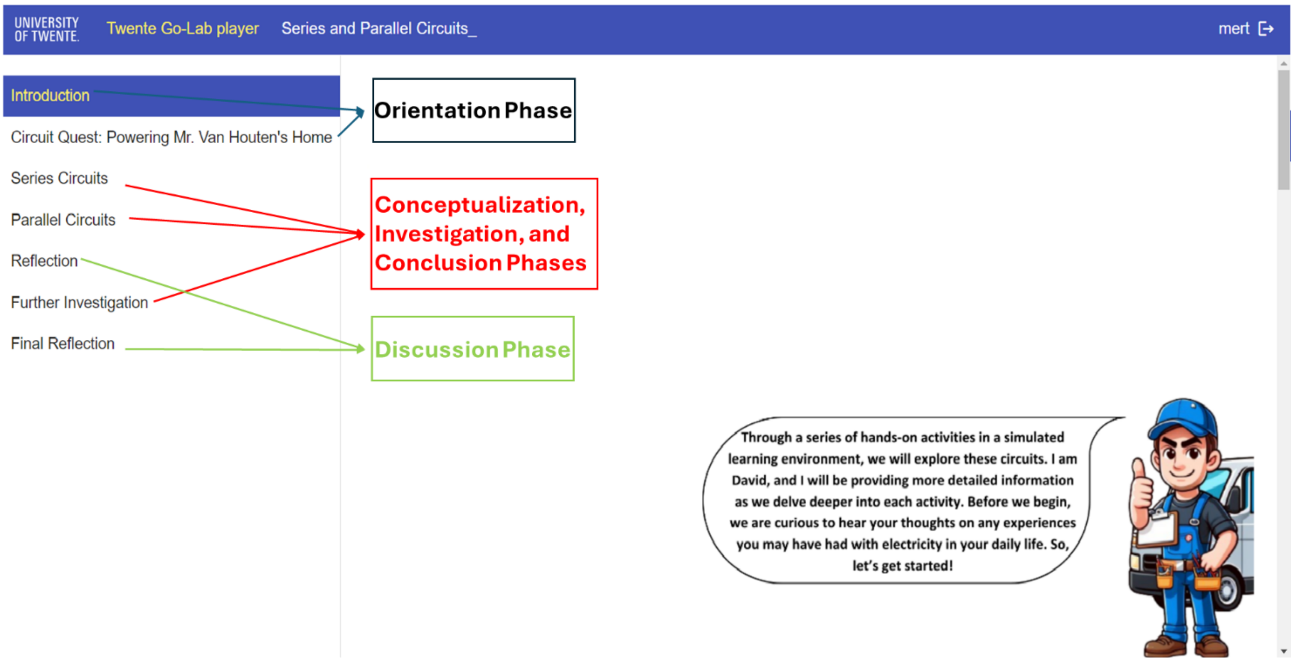
2.3. Materials

2.3.1. IBL Scenario and Environment

IBL environments require challenging scenarios which include solvable questions to effectively engage students and facilitate deep learning (Friesen & Scott, 2013). In this study, an inquiry learning scenario was developed within the context of direct current (DC) circuit electricity. Participants, acting as newly graduated electrical engineers, were tasked with addressing a practical issue in Mr. van Houten's home lighting system. The scenario, aligned with the objectives of the conceptual knowledge test used in this study, not only provides a real-world learning experience but also enhances familiarity with foundational knowledge that bachelor students across various fields possess regarding DC circuits. The topic of DC circuits has been chosen because it involves intricate concepts and problem-solving challenges, making it ideal for IBL.

The learning environment, developed using the Go-Lab platform, has been structured based on Pedaste et al.'s (2015) framework of five inquiry phases: orientation, conceptualization, investigation, conclusion, and reflection. The environment is designed to encompass seven distinct phases: introduction, circuit quest, series circuits, parallel circuits, reflection, further investigation, and final reflection. These phases guide students through the learning process: The orientation phase includes the introduction and circuit quest; the conceptualization, investigation, and conclusion phases involve series circuits, parallel circuits, and further investigation; and the discussion phase incorporates reflection and final reflection (see Figure 1).

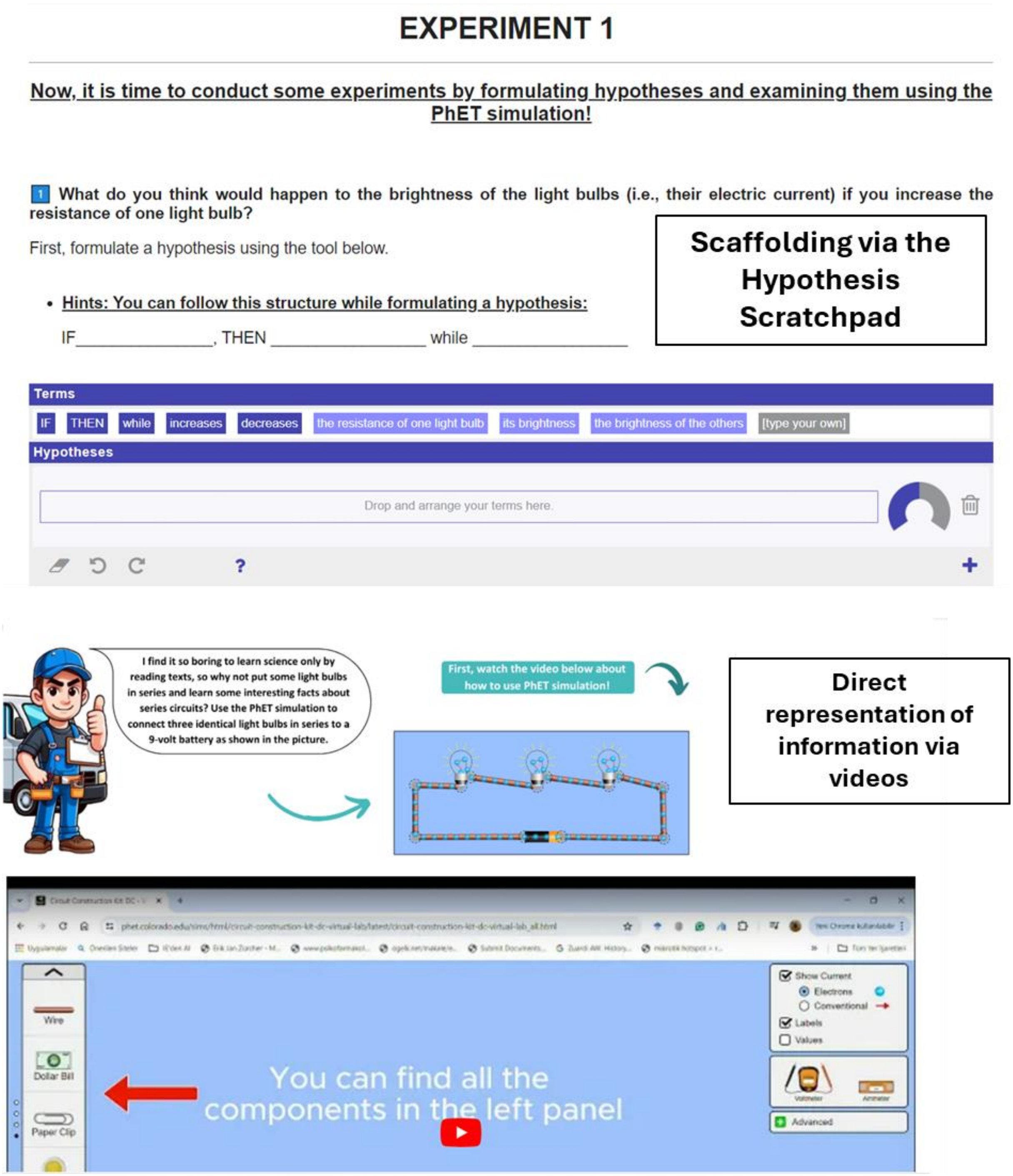
Figure 1



Seven Phases of the Learning Environment Based on Pedaste et al.'s (2015) Framework

Guidance is provided through a combination of scaffolding and direct representation of information. In the present study, generating testable hypotheses is crucial for interpreting data and drawing conclusions (Piekny & Maehler, 2013). Since students often find this process challenging and may not know what a scientific hypothesis looks like (Chang et al., 2008; de Jong & van Joolingen, 1998), scaffolding was provided during the conceptualization phase. This was done using the Hypothesis Scratchpad in Go-Lab to aid in hypothesis generation. Furthermore, direct representation of information has been implemented throughout the inquiry phases by providing textual information, instructional images and videos in a way that facilitates the inquiry and learning process (see Figure 2).

Figure 2



Examples of Guidance Implemented to The Learning Environment

The scenario begins with an introduction by Alex and David, the guides, who engage students by relating the learning objectives to everyday experiences, such as the differences between old and new Christmas lights and the lighting system of battery-powered toys. Students then explore the concept of series and parallel circuits through interactive simulations and guided experiments using the PhET simulation tool. The hands-on activities involve measuring electric current and voltage, formulating and testing hypotheses, and reflecting on observations and outcomes. The tasks are designed to deepen students' understanding of electric current and voltage and the practical applications of series and parallel circuits.

2.3.2. Determining and Interpreting Resistive Electric Circuit Concepts Test (DIRECT)

DIRECT is a 29-item multiple-choice assessment developed by Engelhardt and Beichner (1997; 2004) to measure students' conceptual understanding of direct current resistive electric circuits. It is a valid concept inventory test in the context of science, whose objectives include physical aspects of DC electric circuits, energy, current, and potential difference (voltage) (Engelhardt & Beichner, 2004). Several studies have demonstrated the test's reliability for evaluating university students' conceptual knowledge of DC circuits, with reported Kuder-Richardson formula 20 (KR-20) values of .78 and .71 (Farrokhnia & Esmailpur, 2010; Engelhardt & Beichner, 2004).

For the calculation of the learning performance in the current study, students' raw scores are used, so that a score of 29 is equivalent to 100%. This test has been used both as a pre-test to examine participants' prior knowledge and as a post-test to evaluate their learning outcomes and progress.

2.3.3. Metacognitive Awareness Inventory (MAI)

The MAI, developed by Schraw and Dennison (1994), evaluates how aware students are of their own thinking processes. This inventory has 52 items, using a 5-point Likert-scale format ranging from 1 (always true) to 5 (always false). The MAI encompasses two main parts of metacognition: knowing about one's own thinking (metacognitive knowledge) and being able to manage one's thinking (metacognitive regulation). There are 17 questions about "metacognitive knowledge (α = .78)", which can total up to 85 points, including some items like "I am aware of what strategies I use when I study", and 35 questions about "metacognitive regulation (α = .80)", with a maximum of 175 points, including some items like "I know how well I did once I finish a test". A higher score means a student has better understanding and control of their own thinking processes. Besides these two scores, there is also a total MAI score (α = .79), with a maximum of 260 points (Abdelrahman, 2020).

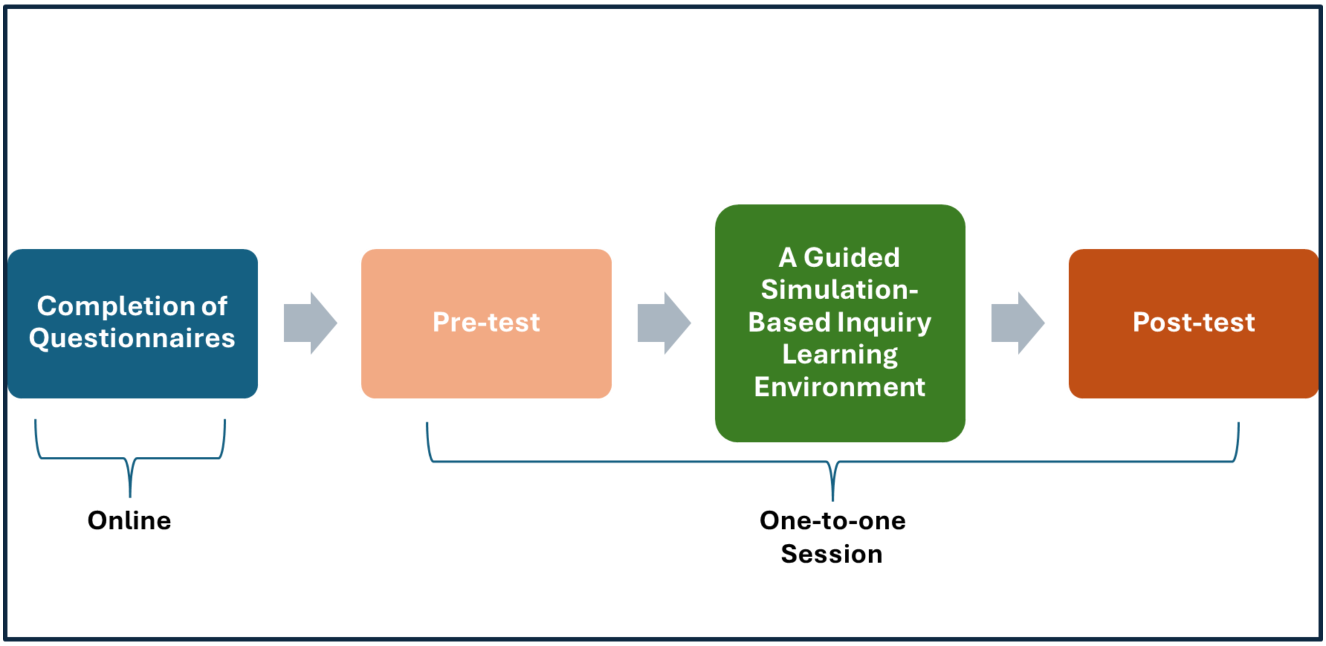
2.3.4. Academic Self-Regulated Learning Scale (ASRLS)

The ASRLS, developed by Magno (2010; 2011) assesses self-regulation skills in higher education and comprises 55 items and 7 subscales. This scale uses a 4-point Likert-scale ranging from 1 (strongly disagree) to 4 (strongly agree). The subfactors of this scale are memory strategy (α = .82) with 14 items like "I record the lesson that I attend to", goal setting (α = .87) with 5 items like "I plan things I have to do in a week", self-evaluation (α = .88) with 12 items like "I welcome peer evaluations for every output", seeking assistance (α = .74) with 8 items like "I study with a partner to compare notes", environmental structuring (α = .78) with 5 items like "I isolate myself from unnecessary noisy places", responsibility (α = .75) with 5 items like "I do things as soon as the teacher gives the task", and organizing (α = .78) with 6 items like "I study at my own pace" (Magno, 2010). The scores can be computed based on means of certain subfactors; that is, higher scores of each subscale indicate the optimum presence of self-regulation skills. In addition to these 7 subscales, a total of self-regulated learning score was calculated, with a maximum of 220 points (Cetin, 2015).

2.4. Procedure

Prior to data collection, ethical approval has been obtained from the ethics commission of the University of Twente. Additionally, all participants have been required to provide informed consent by signing a consent form before participating in the study. Initially, participants have completed a set of questionnaires. These included a demographic questionnaire to collect background information, the MAI to assess metacognitive awareness, and ASRLS to measure self-regulation skills. This initial part has been conducted online by using Google Forms. Participants then have completed the DIRECT as a pre-test to evaluate their prior knowledge. Afterward, students engaged in an interactive simulation-based inquiry learning module designed to teach series and parallel electric circuits through structured guidance and an interactive simulation. Following the learning module, participants undertook the DIRECT one more time to measure the learning outcomes. This part has been carried out in a one-to-one session in the project room at the University of Twente. The entire process spans 2 hours in total (see Figure 3).

Figure 3



Study Procedure Overview

2.5. Data Analysis

All data were analyzed using IBM SPSS Statistics version 26. Before statistical analyses, all quantitative data were screened for missing values and outliers (Tabachnick & Fidell, 2007). All questionnaires were assessed to ensure reliability based on Cronbach's Alpha values between .70 and .95. Results shown that no missing values, and outliers were found in the dataset, except for one outlier in the pre-test score. This issue was addressed by applying a Log10 transformation to the pre-test score, which effectively corrected the anomaly. Moreover, the reliability analysis was conducted for all questionnaires using Cronbach's alpha to evaluate the internal consistency of each subscale. Results indicated that the Cronbach's alpha values for each subscale were from 0.68 to 0.95, which is acceptable. The overall MAI showed a Cronbach's alpha of 0.95, with its subscales Metacognitive Knowledge and Metacognitive Regulation, whose values of 0.89 and 0.93, respectively. Furthermore, the ASRLS subscales demonstrated acceptable reliability with $\alpha = 0.82$ for memory strategy, $\alpha = 0.90$ for goal setting, $\alpha = 0.82$ for self-evaluation, $\alpha = 0.74$ for seeking assistance, $\alpha = 0.68$ for environmental structuring, $\alpha = 0.73$ for learning responsibility, and $\alpha = 0.68$ for organizing. These results suggest that the instruments used in the current study are reliable for evaluating metacognitive awareness and self-regulation.

The data collected from the questionnaires, pre-tests, and post-tests was analyzed using both descriptive and inferential statistics. The primary focus was on understanding the relationships between the independent variables (prior knowledge, metacognitive awareness, and self-regulation skills) and the dependent variable (learning performance). For the first research question, before conducting a multiple linear regression, Pearson's correlation analysis was performed to examine the relationships among variables (e.g., prior knowledge, metacognition, self-regulation, and learning performance). Following this, the regression analysis was conducted to determine if any of these characteristics predict the learning performance.

For the second question, to identify profiles of successful and less successful students in guided simulation-based inquiry learning, we employed hierarchical and k-means clustering analysis after identifying a cut-off point of learning performance for both students group (see Darcan & Badur, 2012; Einolander et al., 2021). This method categorized students based on their levels of prior knowledge, metacognitive awareness, and self-regulation to identify distinct profiles. Initially, we determined the optimal number of clusters (k) to effectively group students with similar characteristics. Subsequently, each student was assigned to a cluster based on their profile similarity. After clustering, we examined the characteristics associated with each cluster to understand how they relate to learning performance. This approach provides insights into the specific attributes that contribute to student success in simulation-based inquiry learning.

CHAPTER 3

Results

The results section was separated into two sections, where the former presented the results related to the first research question and the latter showed the results related to the second research question.

3.1. Contribution of Prior Knowledge, Metacognition, and Self-Regulation to Predicting Learning Outcomes

To provide an overview of the data, the means and standard deviations for prior knowledge, metacognition, self-regulation, and learning outcomes were calculated and are presented Table 3.

Table 3

Descriptive Statistics for Prior Knowledge, Metacognition, Self-Regulation, and Learning Outcomes

Variables	*M*	*SD*
Prior Knowledge	39.43	13.49
Learning Outcomes	48.63	14.36
Metacognitive Awareness Total	183.13	29.22
Metacognitive Knowledge	59.20	10.74
Metacognitive Regulation	123.37	20.19
Self-Regulation Total	153.18	23.02
Memory Strategy	35.50	7.40
Goal Setting	12.60	4.25
Self-Evaluation	35.43	5.70
Seeking Assistance	23.20	4.36
Environmental Structuring	14.60	3.05
Learning Responsibility	13.73	3.01

Organizing	18.10	3.17

***Note**:* Maximum points for prior knowledge/learning outcomes (100), MAI total (260), metacognitive knowledge (85), metacognitive regulation (175), self-regulation total (220), memory strategy (56), goal setting (20), self-evaluation (48), seeking assistance (32), environmental structuring (20), learning responsibility (20), and organizing (24).

Pearson's correlation analysis was performed to test the relationships between independent (prior knowledge, metacognitive awareness, and self-regulation) and dependent (learning outcomes) variables before conducting a regression analysis. Results showed that prior knowledge is positively correlated with the learning outcomes (r = .75, p < .05). Additionally, organizing, a subscale of the self-regulation, also demonstrated a positive relationship with the learning outcomes (r = .39, p < .05). However, no other significant relationships between independent and dependent variables were detected. The relationships between the independent variables (prior knowledge, metacognitive awareness, and self-regulation) are also presented in Table 4.

Table 4

Correlations for Prior Knowledge, Metacognitive Awareness, Self-Regulation, and Learning Outcomes

	1	2	3	4	5	6	7	8	9	10	11	12	13
1-Prior Knowledge	1												
2-Learning Outcomes	**.75****	1											
3-Metacognitive Knowledge	0.03	0.03	1										
4-Metacognitive Regulation	0.08	0.14	.85**	1									
5-MAI Total	0.06	0.10	.93**	.98**	1								
6-Memory Strategy	-0.07	-0.02	.53**	.68**	.65**	1							
7-Goal Setting	-0.04	-0.03	.54**	.63**	.63**	.58**	1						
8-Self-Evaluation	0.18	0.09	.46*	.65**	.59**	.44*	0.22	1					
9-Seeking Assistance	0.13	0.17	0.23	.54**	.43*	.56**	.40*	.68**	1				
10-Environmental Structuring	-0.09	-0.06	.41*	.43*	.46*	.46*	.52**	0.12	.38*	1			
11-Learning Responsibility	0.27	0.22	0.32	.55**	.49**	0.30	.63**	0.29	.43*	.39*	1		
12-Organizing	0.14	**.39***	.40*	.69**	.62**	.66**	.52**	.55**	.75**	.50**	.45*	1	
13-Self Regulation Total	0.08	0.11	.58**	.82**	.76**	.83**	.72**	.68**	.82**	.60**	.61**	.85**	1

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

Based on these results, a multiple linear regression was performed between prior knowledge and organizing as predictor variables and learning outcomes as a predicted variable. The results indicated that the regression model was significant (F (2, 27) = 23.572, p < .05), explaining approximately 64% of the variance in learning outcomes based on prior knowledge and organizing. The regression coefficients shown that prior knowledge (β = .70, *95% CI* [46.08, 94.04], p < .05) and organizing (β = .31, *95% CI* [.30, 2.47], p < .05) were positive significant predictors of learning outcomes (see Table 5).

Table 5

Multiple Regression Analysis Predicting Learning Outcomes from Prior Knowledge and Organizing

		Model				
		R	R^2	F	β	p
Learning Outcomes	Prior Knowledge	.80	.64	23.572***	.70	.000
	Organizing				.31	.014

***p <.001

3.2. Profiles of Successful and Less Successful Students in Guided Simulation-Based Inquiry Learning

Before performing the cluster analysis, the variables were standardized to ensure comparability. Following this, the overall post-test (learning outcomes) score was calculated to classify students into successful and less successful groups. Students with scores above 48.63 mean were coded as successful (n = 14), and those with scores below 48.63 mean were classified as less successful (n = 16). An independent sample t-test was performed to see if the learning performance is different between these two groups. Results indicated that the successful students performed significantly better (M = 60.59, SD = 9.05) than less successful students (M = 38.15, SD = 8.77), t (28) = 27.22, p < .001.

A hierarchical cluster analysis was conducted separately on the standardized variables using Ward's method and Squared Euclidean distance to explore the natural grouping of students based on their levels of prior knowledge, metacognition, and self-regulation. The dendrogram indicated a clear separation into two main clusters for the successful students: Cluster 1 comprised students labeled as 23, 24, 30, 29, 26, and 26 while Cluster 2 included students labeled as 22, 28, 17, 18, 25, 20, 21, and 19. The same process was performed for the less successful students and the dendrogram also revealed a significant separation into two main clusters: Cluster 1 encompassed students labeled as 2, 3, 9, 6, 7, 8, 4, 1, 5, and 12 whereas Cluster 2 involved students labeled as 10, 15, 13, 11, 14, and 16. Based on these distinct separations for both successful and less successful students, it has been confirmed that a two-cluster solution is appropriate for further analysis.

Following the hierarchical cluster analysis, K-means clustering was performed separately with a pre-specified number of clusters (k=2) for successful and less successful students. The final cluster centers for successful students are presented in Table 6. Analyses of the successful student clusters revealed that students in Cluster 1 (Successful Profile 1) possess higher prior knowledge, but lower metacognitive and self-regulation skill scores compared to the mean value for all successful students. Students in Cluster 2 (Successful Profile 2) achieve lower scores on prior knowledge compared to the mean of successful students, but higher scores on almost all metacognitive and self-regulatory skills; i.e., they are more prone to be organized, better at goal setting, evaluating themselves and taking responsibility for their learning compared to the mean values of a successful student.

Table 6

The Final Cluster Centers for Successful Students

Variable	Cluster 1 (N = 5)	Cluster 2 (N = 9)

Prior Knowledge	0.65643	0.42909
Metacognitive Awareness Total	-0.44265	0.59628
Metacognitive Knowledge	-0.42845	0.40568
Metacognitive Regulation	-0.43436	0.65347
Self-Regulation Total	-0.58926	0.74562
Memory Strategy	-0.33811	0.39822
Goal Setting	-0.70630	0.56504
Self-Evaluation	-0.77813	0.54800
Seeking Assistance	-0.45891	0.61699
Environmental Structuring	0.00000	0.27716
Learning Responsibility	-0.44371	0.75430
Organizing	-0.09475	0.91596

Table 7 shows the final cluster centers for less successful students. Analyses of the less successful student clusters shown that students in Cluster 1 (Less Successful Profile 1) have higher scores in metacognitive knowledge, regulation and total metacognitive awareness compared to the mean of the less successful student group. Moreover, they perform better in memory strategy, goal setting, self-evaluation, seeking assistance, environmental structuring, learning responsibility, and organizing. This indicates that while they are still less successful, they possess relatively stronger metacognitive and self-regulation skills compared to Cluster 2. Students in Cluster 2 (Less Successful Profile 2) have significantly lower scores across all variables compared to the mean of the less successful student group. They exhibit lower prior knowledge, metacognitive knowledge, regulation and awareness, memory strategy, goal setting, self-evaluation, seeking assistance, environmental structuring, learning responsibility, and organizing skills.

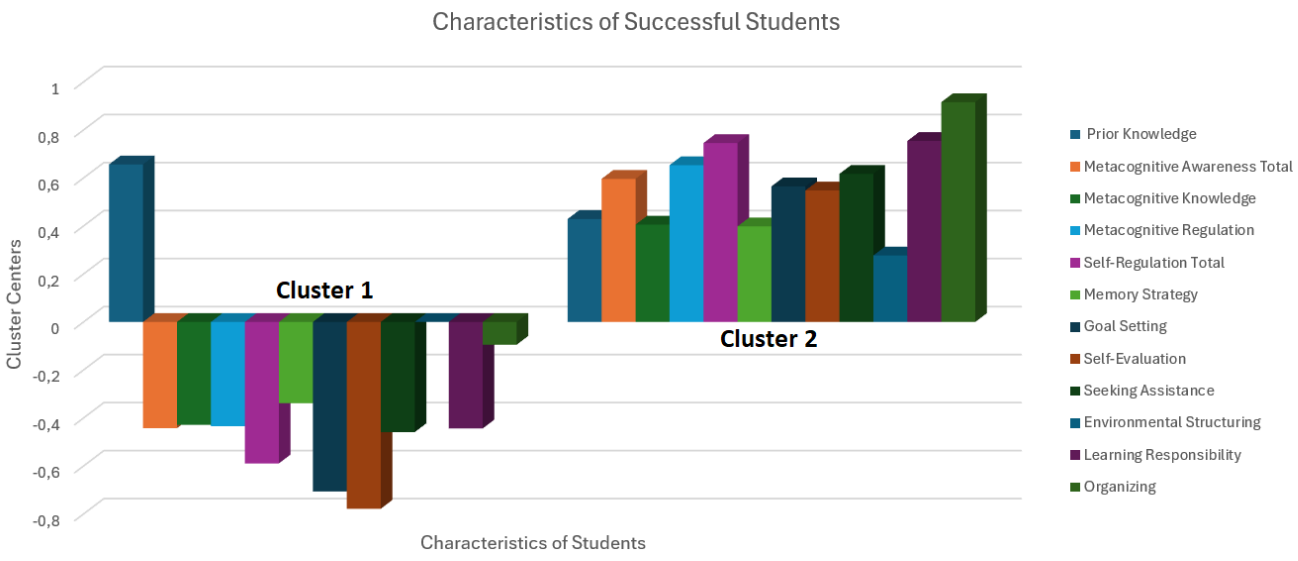
Table 7

The Final Cluster Centers for Less Successful Students

Variable	Cluster 1 ($N = 7$)	Cluster 2 ($N = 9$)
Prior Knowledge	-0.40311	-0.48024
Metacognitive Awareness Total	0.89996	-1.05033
Metacognitive Knowledge	0.91279	-0.87760
Metacognitive Regulation	0.83829	-1.06416
Self-Regulation Total	0.72494	-0.98209
Memory Strategy	0.74384	-0.78892
Goal Setting	0.59867	-0.63828
Self-Evaluation	0.52572	-0.52460
Seeking Assistance	0.44580	-0.70877
Environmental Structuring	0.64706	-0.78043
Learning Responsibility	0.32644	-0.76170
Organizing	0.23914	-1.04931

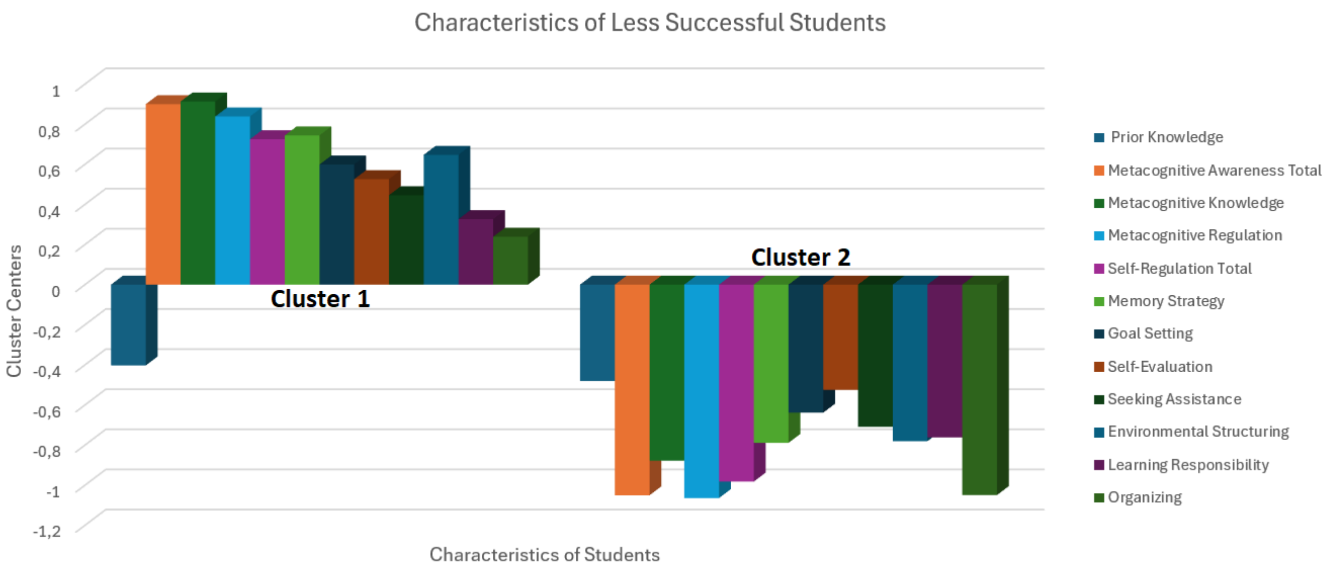
To enhance the understanding of the distinct characteristics of successful and less successful students identified in this study, bar graphs that illustrate the average scores for each variable within each student profile are presented (see Figure 4 and 5). These graphs provide a visual representation of how each profile compares based on the mean score of each cluster within the same profile, highlighting differences between the profiles themselves.

Figure 4



Distribution of Prior Knowledge, Metacognition, and Self-Regulation Among Successful Students

Figure 5



Distribution of Prior Knowledge, Metacognition, and Self-Regulation Among Less Successful Students

CHAPTER 4

Discussion

The current study aimed to investigate the characteristics of successful and less successful students in guided simulation-based inquiry learning within the context of Physics. For this purpose, the characteristics of students that significantly impact learning performance have been identified as prior knowledge, metacognition, and self-regulation. Moreover, a guided simulation-based inquiry learning environment has been developed based on the content of a conceptual physics test called DIRECT, focusing on parallel and series electric circuits. This enabled us to evaluate how these learner factors play a role in both predicting learning outcomes and profiling students in such a learning environment.

4.1. The Impact of Prior Knowledge, Metacognition, and Self-Regulation on Learning Outcomes

Results revealed that both prior knowledge and organizational skills, as a subskill of self-regulation, play a predictive role in learning performance while no other variables were found as a predictive factor in learning outcomes. Among these two variables, prior knowledge was shown to have a higher positive correlation with learning outcomes than organizational skills.

Regarding the role of prior knowledge, it has been seen students with more prior knowledge about a particular topic, such as series and parallel circuits in this study, tended to achieve higher learning performance. This is also consistent with previous studies in the literature regarding the role of prior knowledge in learning outcomes (Alsadoon, 2020; Chen, 2014; Dengel & Magdefrau, 2020; Moré et al., 2015). This positive correlation between prior knowledge and learning performance in the current study supports the constructivist theories of learning, highlighting the importance of students' existing knowledge as a key component of effective learning strategies (Becker, 2002; Bransford et al., 2001; Efgivia et al., 2021; Winters

& Azevedo, 2005). Additionally, the results support cognitive load theory, which suggests that when building upon new knowledge, new information is processed in the working memory with limited capacity and a new cognitive representation of this new knowledge is built in the long-term memory (Sweller et al., 1998). Regarding this, prior knowledge is known as a learner characteristic, suggesting that students with more prior knowledge might have more capacity available in their working memory to process new information and experience a lower cognitive load (Dong et al., 2020; Mihalca et al., 2011; van Riesen, 2018). Therefore, it can be concluded that activating students' prior knowledge facilitates the acquisition of new knowledge, enhancing learning performance.

In the context of guided simulation-based inquiry learning, prior knowledge becomes also crucial. Having a greater level of prior knowledge about parallel and series circuits in this learning environment led to better performance compared to having less prior knowledge. It can be argued that students with higher prior knowledge outperformed their peers because they were able to derive greater benefit from the guidance provided throughout the learning experience. This finding is consistent with existing literature, which suggests that students with higher prior knowledge are more proficient at utilizing guidance to build upon new information, draw conclusions, and ultimately achieve superior performance (Chernikova et al., 2020). However, due to the absence of a control group with an unguided condition, our results can only partially support this conclusion.

Regarding the role of organizing as a crucial subcomponent of self-regulation, it has been observed that students with higher organization skills had better learning performance than those with lower organization skills. This positive relationship between organizing and learning outcomes supports existing self-regulation theories. According to scholars, self-regulation is an important aspect of learner characteristics that facilitates the successful endeavor of personal goals and improves learning performance by reducing cognitive load (Inzlicht et al., 2021;

Seufert, 2020). This is because students can actively structure their meanings, purposes, and methods based on information available in a flexible and adaptable self-regulated learning environment (Bylieva et al., 2021; Paris & Paris, 2001). Considering organizing itself, it encompasses a person's ability to set goals, and systematically follow the necessary steps to accomplish a particular task (Morgan et al., 2016). Knowing how to organize and strategically plan to solve problems and achieve goals is a crucial aspect of effective self-regulation (Gollwitzer et al., 2004). Especially for younger learners, observing and learning how to plan to achieve their goals is linked to greater planning and organizing abilities (Morgan et al., 2016). Furthermore, Zimmerman (2000) highlighted that successful learners are those who effectively organize their work, set clear goals, and employ efficient organizational strategies within a rapidly changing environment. Therefore, it can be claimed that it is important to teach learners how to organize and structure their learning processes to enhance their learning experiences, and eventually learning outcomes.

In the context of guided simulation-based inquiry learning, learners' organizational skills become critical. Having a greater level of organizational skills resulted in better learning performance within this type of learning environment. This is also supported by a constructive approach to learning, which is closely related to IBL, highlighting the role of successful learners taking active role in selecting and organizing information, developing hypotheses, drawing conclusions, and eventually, reflecting on their experiences (Coombs & Elden, 2004). Thus, it can be argued that the findings from this study underline that effective organizational skills enable learners to manage their inquiry tasks more efficiently. This supports the notion that self-regulated learning environments, which promote flexibility and adaptability, are crucial for fostering students' ability to organize their work (Bylieva et al., 2021; Paris & Paris, 2001). Moreover, some of the self-regulatory skills, such as learning responsibility and self-evaluation, also showed a positive correlation, but such a correlation was only significant for organizational skills. This might be attributed to the fact that, for instance, organizational skills directly impact a student's ability to effectively manage and utilize the provided guidance in a structured learning environment, whereas other self-regulatory skills might not have the same immediate effect on performance in this specific context. This is also in line with the notion that learner characteristics, such as organizational skills in this study, are fundamental elements that affect both the design of guidance and its effectiveness (Sun et al., 2022). Thus, theoretical models of simulation-based inquiry learning should incorporate organizational skills as a fundamental component, recognizing their critical role in helping students manage complex and dynamic learning tasks.

4.2. The Characteristics of Successful and Less Successful Students in Guided Simulation-Based Inquiry Learning

The second objective of the current exploratory study was to investigate the characteristics of successful and less successful students in a guided simulation-based inquiry learning environment. The result of analysis revealed four distinct profiles, two for successful and two for less successful students. For successful students, Cluster 1 relies more on prior knowledge, while Cluster 2 benefits from strong metacognitive and self-regulation skills. For less successful students, Cluster 1 has relatively stronger metacognitive skills but needs support in prior knowledge, while Cluster 2 requires comprehensive support across all areas (see Figure 6). Eventually, this indicated that the learner factors play a different role in successful and less successful students in a guided simulation-based inquiry learning environment.

Figure 6

	Successful Students		Less Successful Students	
Characteristics of Students	Cluster 1	Cluster 2	Cluster 1	Cluster 2
Prior Knowledge	Highest	Moderate	Low	Lowest
Metacognitive Skills	Low	High	Highest	Lowest
Self-Regulation	Low	High	High	Lowest

Characteristics of Successful and Less Successful Students in Guided Simulation-Based Inquiry Learning

The significant distinction between the clusters of successful students highlights the diverse pathways to achieving academic success in guided simulation-based inquiry learning environments. According to self-regulation theories, successful students are not homogeneous; rather, they employ different strategies to achieve higher performance (Schunk & Zimmerman, 2012). In this context, it was shown that Cluster 1 primarily relies on their prior knowledge compared to Cluster 2. Further analysis revealed that the prior knowledge of students in Cluster 1 is higher than that of students in Cluster 2 among the successful students and both clusters of less successful students. Nevertheless, their metacognitive and self-regulatory skills were lower than those of Cluster 2 among the successful students and Cluster 1 among the less successful students. These results suggest that having a strong background in a particular topic plays a crucial role in achieving success, corroborating the findings of the first research question. The reliance on prior knowledge in Cluster 1 suggests that having a strong foundation in a particular subject, such as series and parallel circuits, is crucial for engaging and benefiting from this type of complex tasks. This finding is in line with previous study that emphasizes the importance of domain-specific knowledge in facilitating problem solving and application in complex learning environments (Duncan, 2007; Hambrick et al., 2010; Hambrick & Meinz, 2011). Therefore, it can be claimed that prior knowledge is one of the most important characteristics of successful students in such a learning environment.

In contrast to students in Cluster 1, students in Cluster 2 among the successful group demonstrated strong metacognitive and self-regulation skills across all total and subscale scores. Further analysis revealed that Cluster 2 achieved higher scores in these areas compared to both Cluster 1 among successful students and Cluster 2 among less successful students. However, their metacognitive and some self-regulatory skills (e.g., memory strategy, goal-setting, and environmental structing) are lower than Cluster 1 in less successful students. This finding might be partially supported by the results of the first research question in this study. It suggests that metacognitive skills might not be as critical in a guided simulation-based inquiry learning environment. Despite having lower scores in these skills, successful students in Cluster 2 excelled by demonstrating higher scores in skills that are more directly related to learning outcomes, such as organizational skills. Therefore, it might be claimed that in certain educational settings, organizational abilities might play a more important role in students' success than metacognitive awareness. Furthermore, their prior knowledge is less than Cluster 1 in successful students, but higher than both clusters in less successful students. The findings suggest that although Cluster 2 had less prior knowledge compared to Cluster 1 among successful students, they were still classified as successful. This may be attributed to their strong metacognitive and self-regulation skills, which could compensate for their lower prior knowledge in this learning environment. This finding is supported by Minnaert's (1996) study, which highlights the compensatory effect of metacognition in higher education (see also Ohtani

& Hissaka (2018) for a compensation model). According to the compensation hypothesis, it has been stated that students with high metacognitive abilities outperform in complex tasks those with lower metacognitive abilities regardless of their overall aptitude, thereby indicating that metacognitive abilities can compensate for intelligence (Minnaert, 1996). In other words, metacognitive abilities have an additional value on top of intelligence in explaining learning performance. This is also supported by the notion that metacognition can act as a compensatory mechanism for general cognitive abilities (Swanson & Trahan, 1996).

In the context of the present study, the emphasis on metacognitive and self-regulation skills highlights the importance of these skills in managing the demands of simulation-based inquiry learning. Students with strong organizational skills, goal-setting abilities, and self-evaluation techniques are better able to handle the iterative and reflective nature of inquiry tasks. This is supported by the literature, which emphasizes the importance of self-regulated learning activities in IBL (Pedaste et al., 2012). Ucar and Sungur (2017) further highlight that self-regulation is essential for students to effectively manage science inquiry activities, enabling them to control their actions and draw conclusions. This is also corroborated by Seraphin et al.'s (2012) study which noted that metacognition guides students through the thinking processes involved in inquiry, ensuring that they can plan, monitor, and evaluate their understanding and actions. Therefore, it can be asserted that metacognitive and self-regulation skills can enhance students' ability to navigate and benefit from guided simulation-based inquiry learning environments.

On the other hand, the difference between two clusters of less successful students demonstrates how different difficulties students may face in a guided simulation-based inquiry learning environment. The findings indicated that Cluster 1 in less successful students have more prior knowledge than Cluster 2 of less successful students, but less than both clusters of successful students. Additionally, this cluster scored higher on all metacognition and some self-regulation subscales, such as memory strategy, goal-setting, and environmental structing, compared to Cluster 1 among successful students and Cluster 2 among less successful students. These intriguing findings highlight that despite achieving the highest scores in metacognitive skills and certain self-regulation subskills, this group was classified as less successful. Initially, this might seem contradictory, especially considering the compensatory effect of these learner characteristics observed in Cluster 2 of the successful students. However, a closer examination reveals that their prior knowledge is way lower than that of Cluster 2 in the successful students. Consequently, it appears that their advanced metacognitive and self-regulatory skills do not sufficiently compensate for their lack of prior knowledge, leading to poorer performance. This also suggests that students with higher prior knowledge may engage with and benefit from learning processes differently compared to those with lower prior knowledge. For instance, Taub et al. (2014) assert that students with higher prior knowledge are more aware of contextual factors, better at organizing, planning, reflecting on their learning, and adjusting their understanding of the question than those with lower prior knowledge. This has been explained by Winne and Hadwin's Self-Regulated Learning model which suggests that higher prior knowledge leads to be more effective at self-regulating since students with higher prior knowledge have more relevant knowledge that enables them to build new knowledge upon their existing background (Mayer, 2004; Winne & Hadwin, 2008). Pass et al. (2003) also clarify this by proposing that students with higher prior knowledge have more working memory capacity to allocate more time for metacognitive monitoring and selecting metacognitive strategies.

Within this study, the findings support the importance of having sufficient prior knowledge to benefit from metacognitive and self-regulatory skills throughout guided simulation-based inquiry learning. Even though the relationships among prior knowledge, metacognition and self-regulation in such a learning environment have not been explicitly addressed before, it can be deduced from the existing literature that prior knowledge might mediate the relationship between metacognitive and self-regulatory skills and learning performance in this context (see Mayer, 2004; Pass et al. 2003; Winne & Hadwin, 2008). Therefore, it can be alleged that without sufficient foundational knowledge, even students with strong metacognitive and self-regulatory skills may struggle to achieve high levels of performance in complex learning tasks.

When considering the characteristics of Cluster 2 in less successful students, it is evident that they scored the lowest in nearly all domains compared to other clusters. As previously mentioned, the results highlight the importance of prior knowledge, metacognition, and self-regulation in achieving better a better performance (see Abdelrahman, 2020; Barnard-Brak et al., 2010; Shing & Brod, 2016; Wang et al., 2010). This cluster exemplifies the struggles of learners who lack foundational knowledge, metacognitive and self-regulation skills.

The findings are also in line with the existing literature in the context of the current study. Regarding this, Kaiser et al. (2018) denote that students with lower prior knowledge have poor performance in an IBL environment. Additionally, Ben-David and Zohar (2009) claim that students' metacognitive abilities should be improved in order to do the scientific inquiry processes. Lastly, Lai et al. (2018) demonstrated that low self-regulated learners showed significantly lower achievement than those with higher self-regulation in science inquiry on learning outcomes. Based on these findings, therefore, it can be claimed that students who lack prior knowledge, metacognitive skills, and self-regulation abilities may struggle with acquiring new knowledge, monitoring their cognitive processes, and regulating their learning activities.

4.3. Implications for Practice

This section was organized into two main parts. The first part discusses the implications of prior knowledge and organizational skills as key predictors of learning performance, highlighting how these factors can enhance student learning outcomes. The second part focuses on the importance of clustering students based on their prior knowledge, metacognitive and self-regulation skills, providing insight into how targeted interventions can be designed to support different student groups more effectively.

4.3.1. Practical Implications for Prior Knowledge and Organizational Skills for Learning Performance

Results suggest several actionable strategies for educators who want to develop an effective guided simulation-based inquiry learning environment. First, it is important to evaluate students' prior knowledge before engaging them in inquiry-based tasks. This can be done through multiple choice tests, open questions, association tests, recognition tests or free recall that identify knowledge gap (Dochy et al., 2002; Menshakova, 2023). By understanding this knowledge gap, educators can tailor their instructional approaches to provide more efficient learning environments. Additionally, incorporating activities that activate and build on prior knowledge can significantly improve learning performance. For instance, concept mapping and analogies provided throughout the learning experience can help students connect new information to their existing background, increasing learning efficiency (Farrokhnia et al., 2023; 2023b; Gurlitt & Renkl, 2009; Hassanzadeh et al., 2016; Hatami et al., 2016; Sidney & Thompson, 2019). Lastly, providing differentiated guidance depending on students' prior knowledge can optimize learning for all students, as it has been known that the benefits from guidance can vary among students, thereby impacting learning outcomes (see Brenner et al., 2017; Chernikova et al., 2020). In summary, assessing students' prior knowledge in guided simulation-based inquiry learning environments can lead to more effective and personalized learning experiences. By aligning instructional approaches with students' prior knowledge, educators can facilitate deeper learning, reduce cognitive load, and improve overall learning performance.

Furthermore, educators can follow several strategies to boost students' organizational skills within guided simulation-based learning environments. Educators should design IBL activities that incorporate training in organizational skills. This can include teaching students how to set clear goals, break down tasks into smaller steps, and develop strategies for completing inquiries (e.g., Hattie & Donoghue, 2016; Van Der Hoek, 2016). Providing students with tools such as checklist, timelines, and organizers can enhance learning performance in guided simulation-based inquiry learning environments. Moreover, to help students develop strong organizational skills, educators can provide scaffolding as guidance that fades as students become more proficient (Lazonder & Harmsen, 2016). Initially, teachers might provide detailed instructions and templates for organizing tasks throughout the inquiry learning. Over time, they can encourage students to take more responsibility for planning and organizing their IBL science activities, such as developing hypotheses, collecting data and drawing conclusions. Lastly, implementing digital tools and platforms that facilitate organization can improve students' ability to manage their learning activities. For instance, integrating a tracking system for monitoring progress and tasks into guided simulation-based inquiry learning environments can provide support for developing organizational skills, eventually enhancing learning performance (Dignath et al., 2023). In short, organizational skills as a subcomponent of self-regulation are crucial for optimizing learning performance in such a learning environment. By incorporating IBL activities, scaffolding and digital tools that improve organizational skills, educators can enhance students' ability to manage their learning activities effectively, and ultimately, achieve better academic outcomes.

4.3.2. Importance of Clustering Students in Educational Settings and Its Practical Implications

Clustering is a process of grouping a set of characteristics into classes of similar groups, which provides a collection of data objects that are similar to each other within the same cluster (Govindasamy & Velmurugan, 2018). Clustering students based on their characteristics, such as prior knowledge, metacognitive skills, and self-regulation abilities, in the context of learning systems is crucial in educational settings since it offers in-dept information for teachers to provide more adaptive scaffolding and learning environments (Bouchet et al., 2013). Based on clustering, describing students' profiles of conceptions of learning is considered as a fundamental pre-requisite to offer more personalized learning environments to enhance the effectiveness of learning (Vettori et al., 2020). Regarding this, several studies in educational area have been conducted to classify students' performance by using different algorithms of clustering. For instance, k-means algorithm for clustering has been used many times to profile students based on their performance to improve their academic success in higher education (e.g., Rana & Garg, 2016; Saxena et al., 2009). This analysis has been also used for other purposes, such as for profiling student engagement and motivation (Einolander et al., 2021), or students' conceptions of learning (Vettori et al., 2020). The findings from these studies point out that clustering students enables educators to utilize instructional strategies to meet the various needs of learners, thus enhancing learning outcomes. It can be stated that understanding these profiles can help in designing interventions that address specific deficiencies and enhance individual strengths, ultimately supporting all students in achieving their full potential.

To further improve the learning outcomes of students based on their clusters, the following practical interventions are proposed and can be implemented to address their specific strengths and areas for improvement in a guided simulation-based inquiry learning environment.

Personalized learning, referring a variety of instructional methods that are proposed for specific needs and interests, is important to maximize student engagement and academic achievement (Lu & Churchill, 2013; Zheng, 2018). Different student profiles can benefit from tailored learning activities. To illustrate, students with high prior knowledge can be provided with learning activities that challenge their understanding and allow them to apply different concepts in practice. These might include advanced problem-solving tasks, case studies, and opportunities to deal with in real-world scenarios. On the other hand, students with strong metacognitive and self-regulatory skills can benefit from complex and open-ended tasks that enable them to effectively plan, organize, monitor and evaluate their learning progress. Providing personalized learning activities will ensure that each student is challenged and supported appropriately throughout their learning activities in a guided simulation-based inquiry learning environment.

Strong prior knowledge is fundamental to effective learning, particularly in complex inquiry-based tasks (Richter et al., 2022). Therefore, it is crucial to build foundational knowledge before introducing these complicated tasks. This ensures that students can actively engage with the problems and benefit from the guidance provided simultaneously (van Riesen et al., 2018). In such a learning environment, educators can provide support through tutoring and supplementary materials to reinforce foundational concepts. This enables students to have a strong foundational base, which eventually allows them to engage more effectively with advanced simulation-based inquiry tasks (please see section 4.3.1 for more detailed intervention plans of prior knowledge).

Metacognitive and self-regulation skills are critical for successful learning, especially in a guided simulation-based inquiry learning (Liu et al., 2014; Rahimi et al., 2015; Seraphin et al., 2012). Therefore, these skills can be integrated into the curriculum through explicit instruction provided by teachers on organizing, goal setting, planning, and self-evaluation. This can be done through by asking questions about particular tasks, suggesting pertinent domain-independent strategies, or multiple strategy programs (see Dabarera et al., 2014; Roll et al., 2012). This will encourage students to reflect on their learning processes and develop effective strategies. By incorporating these skills into the curriculum, educators will help students become more independent learners, capable of managing their own learning and tackling challenges.

4.4. Conclusion

In conclusion, this exploratory study investigated the characteristics of successful and less successful students in guided simulation-based inquiry learning within Physics education. By identifying prior knowledge, metacognition, and self-regulation as learner characteristics, the results highlight the different roles of these factors in achieving academic success in such a learning environment. It was found that prior knowledge and organizational skills, a subcomponent of self-regulation, are significant predictors of learning outcomes. Furthermore, the cluster analysis revealed four distinct student profiles, underlining the importance of personalized instructional strategies depending on their strengths and weaknesses. One of the most unique findings of the study is that that while prior knowledge is important, it can be compensated by strong metacognition and self-regulation skills to achieve sufficient success. Nevertheless, this compensatory effect appears to be dependent on having a certain amount of prior knowledge. Therefore, the practical implications of these findings emphasize the need for educators to assess and build upon students' prior knowledge and enhance metacognitive and self-regulation skills while developing and implementing this kind of learning environment into the curriculum. By applying these strategies, educators can create more effective and engaging learning environments that support all students in reaching their full potential in guided simulation-based inquiry learning contexts.

4.5. Limitations and Suggestions for Future Research

One of the primary limitations of the present study is the small sample size, which consisted of 30 participants. A small sample size can limit the generalizability of the findings, restricting the usefulness of the scientific conclusions (Van de Schoot & Miocević, 2020). Thus, the results might not be representative of the larger population. Furthermore, a small sample size reduces the statistics power of the study, making it more difficult to detect significant relationships between variables and reducing the chance of determining a true effect (Button et al., 2013).

This might explain why we could not find other predictive variables of learning performance in addition to prior knowledge and organizing. To address this limitation, future research should focus on including a larger and more diverse sample size, potentially incorporating participants from different educational levels, such as high school. This will ensure more generalizable and a clearer understanding of the impact of learner factors on learning outcomes.

Another limitation of this study is only using of a guided simulation-based inquiry learning environment. By not incorporating an unguided learning condition, it is less likely to discern how students' characteristics might differ depending on the level of guidance. This is because it has been known that students' performance might vary with the amount of guidance provided (e.g., Furtak et al., 2012; Moreno, 2004). Hence, the absence of an unguided condition might limit the understanding of how the learner factors interact with the amount of guidance in such a learning environment. To overcome this limitation, future studies should include both guided and unguided conditions to compare the effects of these conditions on learning performance and determine the relationships between the characteristics of students and student performance, depending on the amount of guidance. One effective solution for this would be to employ Solomon's Four-Group design (see Solomon, 1949), which controls for the potential effects of repeated testing on the results, providing more insight into the role of guidance in this kind of learning environment.

A further limitation of this study is its exclusive focus on the relationships between the characteristics of students and learning performance, without incorporating the learning analytics and analytical reports provided by the Go-Lab environment. Learner analytics in the Go-Lab aims to collect and analyze user activities, such as log protocols and the time spend in phases, and answers in applications, to improve a learning experience (Hecking & Cao, 2014). By not including this data, the study might have missed valuable insights into student behaviors and interactions with a guided simulation-based inquiry learning environment. To deal with this limitation, future studies should integrate learning analytics to the descriptive and quantitative analyses. Moreover, together with these learning analytics provided by Go-Lab, students' emotions can be measured by using face recognition system since it has been known that emotions play a crucial role in learning performance (Sahraie et al., 2024). Eventually, all these potential variables in learning performance, including user activities, analytical reports and emotions, can be used by educators for designing better IBL scenarios in the future studies.

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