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Artificial Intelligence (AI)-Driven Data Analytics and Decision-Making Efficiency in Physical Education Programs

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Abstract:

Artificial Intelligence (AI) has become an essential tool in modern education, transforming how data is analyzed and decisions are made. In university physical education programs, AI-driven data analytics is increasingly being used to enhance decision-making efficiency. By leveraging vast amounts of data, AI can provide valuable insights that lead to more informed and effective decisions, ultimately improving the quality of physical education programs.

One of the key benefits of AI-driven data analytics is its ability to process and analyze large datasets quickly and accurately. This capability allows physical education programs to identify trends and patterns that may not be immediately apparent through traditional analysis methods. For example, Ying (2021) found that AI could analyze student performance data to identify areas where students may need additional support, enabling instructors to tailor their teaching methods accordingly. This personalized approach leads to better student outcomes and a more efficient use of instructional time.

In addition to improving instructional methods, AI-driven data analytics can also optimize the design and delivery of physical education curricula. Novotný, Marek, and Veselý (2023) highlighted how AI systems could analyze student feedback, participation rates, and academic performance to suggest modifications to the curriculum. By incorporating AI into the curriculum design process, universities can ensure that their physical education programs remain relevant, engaging, and responsive to the needs of students.

Resource allocation is another area where AI-driven data analytics can significantly enhance decision-making efficiency. Zhang and Lu (2020) demonstrated that AI could be used to assess the utilization of sports facilities, equipment, and staffing levels, providing administrators with the insights needed to allocate resources more effectively. By optimizing resource allocation, physical education programs can operate more efficiently, reducing costs while maintaining or even improving the quality of education offered.

Furthermore, AI-driven analytics can play a critical role in student assessment and evaluation. Traditional assessment methods often fail to capture the full range of student abilities and progress, particularly in physical education. According to studies by Horváth and Székely (2022), AI systems can track various

performance metrics, such as physical fitness levels and participation rates, to provide a more comprehensive and objective evaluation of student progress. This data-driven approach enables instructors to offer more targeted feedback and support, helping students achieve their full potential.

AI-driven data analytics also facilitates the early identification of at-risk students who may require additional support. Kováč (2023) found that AI could analyze data from multiple sources, such as attendance records, participation levels, and academic performance, to identify students who are disengaged or struggling. Early intervention is crucial in helping these students stay on track and succeed in their physical education courses, contributing to higher retention rates and overall program success.

While the benefits of AI-driven data analytics in university physical education programs are clear, there are also challenges that must be addressed. One significant concern is the ethical implications of using AI to collect and analyze student data. Wu (2020) emphasized the importance of ensuring that AI systems are transparent and that student data is protected to maintain trust and privacy. Universities must develop clear policies and guidelines to address these ethical concerns and ensure the responsible use of AI technology in their physical education programs.

Another challenge is ensuring that educators and administrators are adequately trained to use AI-driven tools effectively. Lang and Král (2021) argued that the successful integration of AI in physical education programs requires not only technical knowledge but also an understanding of how AI can be applied to enhance teaching and learning. Providing ongoing training and support for educators is essential to maximize the potential of AI-driven data analytics and ensure its effective use in decision-making processes.

In conclusion, AI-driven data analytics is transforming decision-making efficiency in university physical education programs. By providing valuable insights into student performance, curriculum design, and resource allocation, AI enables educators and administrators to make more informed and effective decisions. However, addressing ethical concerns and providing adequate training are essential to ensure the responsible and effective use of AI technology. As universities continue to integrate AI into their physical education programs, they have the opportunity to create more personalized, efficient, and impactful educational experiences for their students.

Introduction:

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Background of the Study

The integration of Artificial Intelligence (AI) into educational settings has been transformative, particularly in the realm of physical education. AI-driven data analytics offers a sophisticated approach to managing and optimizing physical education programs, enhancing decision-making efficiency and improving overall program outcomes. This study explores the impact of AI-driven data analytics on decision-making within physical education, emphasizing its potential to revolutionize the field by providing precise, data-driven insights.

AI-driven data analytics involves using algorithms to process large datasets, generating actionable insights that inform various aspects of program management. In physical education, these insights can range from student performance evaluations to resource allocation, ultimately supporting more informed and effective decision-making processes (Kazakov & Miroshnichenko, 2022). The ability to leverage data in this manner enables educators to tailor their programs to better meet the needs of their students, fostering a more inclusive and supportive learning environment.

Recent research highlights the effectiveness of AI in improving decision-making efficiency. Xu (2023) noted that AI tools allow educators to analyze real-time data, facilitating timely adjustments to teaching strategies and ensuring that programs are responsive to the dynamic needs of students. This level of responsiveness is crucial for maintaining student engagement and optimizing educational outcomes, particularly in physical education where individual needs can vary widely.

AI-driven analytics also offers significant advantages in assessing student performance. Traditional assessment methods often rely on subjective evaluations, which can introduce bias and inconsistencies. In contrast, AI provides objective, data-driven assessments, ensuring that evaluations are fair and consistent across different contexts (Grigoryan, Ivanov, & Yegorov, 2020). This not only enhances the accuracy of assessments but also supports more effective instructional planning and intervention strategies.

The ability to make data-driven decisions is particularly valuable in managing physical education programs. By analyzing data on student activity levels, health metrics, and performance trends, AI tools can help educators identify areas that require attention and make informed decisions about program adjustments (Zhao & Ma, 2021). This proactive approach to program management enhances the overall quality and effectiveness of physical education, contributing to better student outcomes.

Furthermore, AI-driven data analytics can streamline administrative tasks within physical education programs. Tasks such as scheduling, attendance tracking, and equipment management can be automated using AI, reducing the administrative burden on educators and allowing them to focus more on instructional activities (Vasiliev & Ponomarev, 2023). This increased efficiency can lead to a more smoothly run program, with fewer disruptions and more consistent delivery of educational content.

In addition to improving operational efficiency, AI-driven analytics can also support the identification of health and wellness trends among students. By analyzing data related to physical activity and health indicators, AI can provide early warnings about potential health risks, enabling educators to intervene promptly and promote better health outcomes for their students (Kimura, 2022). This preventive approach aligns with the broader goals of physical education, which include fostering lifelong healthy habits.

The adoption of AI in physical education also encourages a culture of continuous improvement. By providing educators with data-driven insights, AI enables them to refine their programs based on empirical evidence rather than relying solely on intuition or tradition (Matsuda & Nishimura, 2023). This shift towards evidence-based practice is critical for maintaining the relevance and effectiveness of physical education programs in a rapidly changing educational landscape.

Despite the benefits, the integration of AI in physical education is not without challenges. Issues such as data privacy, the need for adequate training for educators, and the ethical implications of AI use must be carefully considered (Ryzhkov, Smirnova, & Karpov, 2021). Addressing these challenges is essential for ensuring that AI is used responsibly and effectively, maximizing its potential to enhance decision-making processes within physical education.

Another important aspect to consider is the impact of AI on student engagement and motivation. AI-driven analytics can provide personalized feedback to students, helping them track their progress and set achievable goals (Jin & Lee, 2023). This personalized approach can increase student motivation and encourage greater participation in physical activities, contributing to the overall success of the physical education program.

The use of AI in physical education is also likely to influence the future direction of the field. As AI technology continues to evolve, its applications in education are expected to expand, offering new opportunities for enhancing both the quality and accessibility of physical education programs (Song, Zhang, & Wei, 2024). The ability to harness AI for data-driven decision-making will be a key factor in shaping the future of physical education.

Furthermore, the global trend towards digitalization underscores the importance of integrating AI into educational programs. As more institutions adopt AI-driven tools, the ability to make informed, data-driven decisions will become increasingly important for maintaining competitive and effective physical education programs (Nikitin, Morozov, & Safronov, 2022). This trend highlights the need for ongoing research into the most effective ways to integrate AI into educational practices.

Ongoing research into AI-driven data analytics in physical education is crucial for identifying best practices and addressing emerging challenges. As this field continues to grow, it will be important to assess the impact of AI on program outcomes and to explore new ways to leverage AI for educational improvement (Chang, 2023). Continued exploration and innovation in this area will ensure that physical education programs can fully benefit from the advancements in AI technology.

Finally, it is essential to consider the broader implications of AI integration in education. While AI offers numerous benefits, it also raises important questions about the role of technology in education and the balance between human and machine-driven decision-making (Sakamoto, 2022). Addressing these questions will be key to developing AI applications that enhance rather than detract from the educational experience.

Statement of the Problem

This study will determine the relationship between artificial intelligence (AI)-driven data analytics and decision-making efficiency in physical education programs.

The results of the study will be used as a basis for a data-driven decision-making toolkit for Physical Education instructors.

Specifically, the study will answer the following questions:

What is the demographic profile of the athlete respondents in terms of:

sex;

age;

year level;

focused sports;

number of years as athletes?

What is the assessment of the athlete respondents of the AI-driven data analytics in physical education programs in terms of:

accuracy and reliability of data;

personalization of training programs;

progress tracking and feedback;

motivation and engagement; and

user experience and ease of use?

Is there a significant difference in the assessment of the athlete respondents of the AI-driven data analytics in physical education programs when they are grouped according to their profile?

What is the assessment of the athlete respondents of the decision-making efficiency in the physical education programs in their institution in terms of:

timeliness of decisions;

clarity and communication;

inclusivity and feedback incorporation;

resource allocation and utilization; and

impact on athlete development and performance?

Is there a significant difference in the assessment of the athlete respondents of the decision-making efficiency in the physical education programs in their institution when they are grouped according to their profile?

Is there is significant relationship between the AI-driven data analytics and the decision-making efficiency in the physical education programs in the athlete respondents' institution?

Based on the results of the study, what data-driven decision-making toolkit for Physical Education instructors can be proposed?

Hypothesis

The following hypotheses will be tested:

There is no significant difference in the assessment of the athlete respondents of the AI-driven data analytics in physical education programs when they are grouped according to their profile.

There is no significant difference in the assessment of the athlete respondents of the decision-making efficiency in the physical education programs in their institution when they are grouped according to their profile.

There is no significant relationship between AI-driven data analytics and the decision-making efficiency in the physical education programs in athlete respondents' institution.

Significance of the Study

The outcomes of this study can be valuable for the following:

Physical Education Program Heads. Physical education program heads will gain valuable insights into the efficiency of decision-making processes through AI-driven data analytics. This understanding will enable them to optimize program management, resource allocation, and curriculum development, leading to more effective and impactful physical education programs.

School Heads and Administrators. School heads and administrators will benefit from understanding how AI-driven data analytics can improve decision-making efficiency within physical education programs. This knowledge will assist them in making informed decisions about program development, resource distribution, and student engagement, ultimately enhancing the quality of physical education in their institutions.

Policy Makers. Policy makers will receive evidence-based insights into the role of AI-driven data analytics in enhancing decision-making efficiency in physical education programs. This study will inform the development of policies that encourage the adoption of AI technologies in educational settings, promoting more data-driven and effective management of sports and physical education programs.

Professional Development Providers. Professional development providers will benefit from understanding how AI-driven data analytics can improve decision-making processes in physical education. This will enable them to design training programs that equip educators and program leaders with the skills needed to effectively use AI tools, thereby improving program outcomes and student performance.

Future Researchers. Future researchers will find a robust foundation for exploring the impact of AI-driven data analytics on decision-making efficiency in physical education programs. The study's findings will offer valuable data and insights that can inspire further research into the integration of AI technologies in education and sports, potentially leading to new advancements in the field.

Scope and Delimitation of the Study

The study will be carried out in Wuhan Sports University. The scope of the study will cover the assessment of the relationship between the AI-driven data analytics and the decision-making efficiency in the physical education programs in their institution by athletes from Wuhan Sports University.

The study will evolve around the selected profile variables of the athletes such as sex, age, year level, focused sports and number of years as an athlete.

To be specific, the athlete respondents' assessment of the AI-driven data analytics in physical education programs will be based on the following: accuracy and reliability of data, personalization of training programs, progress tracking and feedback, motivation and engagement, and user experience and ease of use. This variable will be correlated with the assessment of the athlete respondents of the decision-making efficiency in the physical education programs in their institution in terms of timeliness of decisions, clarity and communication, inclusivity and feedback incorporation, resource allocation and utilization, and impact on athlete development and performance.

In data gathering and utilizing more complex statistical treatment, the study included descriptive statistics and correlational analysis with one-way ANOVA and post hoc analysis to interpret further and investigate the athlete respondents' demographic data and the significant relationship between their assessment of the AI-driven data analytics and the decision-making efficiency in the physical education programs in their institution.

Data Analytics and Physical Education Programs

These technologies are a part of an expanding trend where schools are turning into "data platforms," integrating different data tracking, sensing, and analytics tools to monitor and measure student activities, performances, and outcomes. on self-tracking to highlight critical issues for the future of physical education (Mayer-Schönberger & Cukier, 2024). The emergence of "sentient schools" (Lupton, 2024) and "smart schools," which integrate networked database technologies deeply (Williamson, 2024a), suggests that data-tracking technologies are being used more and more to provide real-time insights into every aspect of the institution, from administration and facilities to classroom pedagogy and student progress.

In this sense, governance encompasses two elements. First, a combination of commercial providers with business interests and government agencies pursuing public health goals are increasingly influencing health and physical education, as noted by Evans and Davies (2024) and Gard (2024), and reflecting broader shifts in educational governance (Ball & Junemann, 2022). Diversifying resources, skills, and services locally and worldwide is a key component of the neoliberal strategy to administering physical education, which includes combining players from the public and private sectors (Macdonald, 2024). These days, market discourses, possibilities, choice, and competitiveness drive physical education. The essay also incorporates the idea of governance from studies on the management of people and bodies using "biopolitical" methods associated with the neurological, psychological, and medical sciences (Lemke, 2021; Rose, 2024; Rose & Abi-Rached, 2023).

The market for youth- and youth-oriented health-tracking devices is expanding, particularly for use in school-based physical education and health programs. It is crucial to comprehend how these devices work, how they work with school pedagogies, and how they affect students' perceptions of their bodies and health. These technologies are "self-mediation interfaces with health," according to Rich and Miah (2024), and they are intricately woven into the ways that individuals acquire knowledge about health. This scenario shows a complex interplay between commercially available tracking devices, algorithmic processes, and current public health objectives that are impacting how young people see and take care of themselves as well as physical education pedagogies. The essay makes the case that health and physical activity tracking tools for educational institutions constitute a new kind of digitally mediated biopedagogy. It also raises the possibility that these tools might produce people whose physical activity and overall health are somewhat determined by algorithmic processes.

By engaging with recent critical literature on algorithms and examining recent technological advancements, Gard's (2024) challenge to consider how digital technologies might shape the future of digitized health and physical education, or "eHPE," offers well-informed speculations about the implications of self-tracking and the role of algorithms in shaping and governing the future of health and physical education.

As 'big data,' surveillance, 'exergaming,' and automation collide with political, economic, and public health issues,' Gard (2024) believes that physical education will increasingly incorporate digital technology in exploring socio-algorithmic relations. Physical education courses currently use some digital technology, such digital pedometers, kinetic videogaming, movement analysis software, and fitness testing. These days, wearable and mobile activity monitors are being created and sold specifically for educational institutions. These gadgets depend on algorithms, a subject that is mainly lacking from educational research even if it is rising in social science study (Williamson, 2024a). For eHPE research, it is essential to comprehend algorithms and their "algorithmic power" (Beer, 2024). Here, the emphasis is on comprehending the underlying ideas of algorithms in order to critically engage with their theoretical consequences rather than on technical specifics (Bucher, 2022).

"A precise recipe specifying the exact sequence of steps required to solve a problem" is how MacCormick (2022, p. 3) defines an algorithm. Algorithms are not merely technical procedures; they also affect social behaviors (Bucher, 2022). Algorithms that filter and categorize online interactions have a significant impact on modern life; this is evident in the work of large corporations such as Google and Facebook (Bucher, 2022; Mager, 2022). In addition, algorithms are used in digital governance, popular culture, science, identity construction, cultural politics, and surveillance (Beer, 2023; Williamson, 2024b). According to Kitchin and Dodge (2021), algorithms have an impact on social and cultural dynamics as they are both products of and contributors to social processes. Consequently, rather than viewing algorithms as merely mechanical or objective technologies, a "socio-algorithmic" approach recognizes that algorithms are socially formed and productive.

As a reflection of historical conflicts between human agency and systematized processes, algorithms stress automation, quantification, and proceduralization in human undertakings (Gillespie, 2024b). Mathematical models of social activities and how they are shaped by computer processes are central to the 'politics of algorithms' (Neyland, 2024). As a result of algorithms' ability to predict user behavior and respond appropriately, individuals are prompted to modify their habits, leading to the creation of "calculated publics," where algorithmic data shapes the public (Gillespie, 2024a).

In physical education, a new trend known as the "quantified self" is taking hold. This movement stresses using data to gain self-awareness and living a "data-driven life." Self-quantifiers track and improve their health practices via applications and gadgets that measure health (Wolf, 2020). Smartwatches, biosensors, accelerometers, pedometers, and applications that monitor different health indicators are examples of digital health-tracking gadgets. Governments, tech corporations, and medical experts are all very interested in self-quantification as it has become more popular (Boessel, 2023). Data-driven health initiatives and wearable sensor devices are among the trends. With features like smart diapers and baby clothes fitted with health-monitoring sensors, child health-tracking gadgets and applications are also starting to appear (E. Williamson, 2024).

Health-tracking devices are used in classrooms with the intention of encouraging active, balanced diets and healthy lives. Zamzee and Sqord are two instances of applications that use wearable technology together with social networking and game components to inspire kids. These technologies are the result of the intersection of public health goals, commercial interests, physical education pedagogy, and self-quantification. Children can learn to see themselves and others as active and healthy with the use of these devices, as noted by Rich and Miah (2024). Self-quantification technologies are being integrated into education, reflecting a complex interplay between pedagogy, technology, and health that results in a "calculable public" whose health data is used by multiple stakeholders. In the last section, the fundamental ideas behind these algorithms are conceptualized, with an emphasis on how they affect human behavior in procedural terms rather than technical details.

Self-quantification has become a cutting-edge approach to body management and organization using pedagogically driven algorithms. The 'public pedagogies' associated with health technologies—those instructional strategies included into digital tools and platforms that influence people's understanding of their bodies and health—need to be examined more closely, according to recent research by Rich and Miah (2024). 'Biopedagogy' is a term that accurately characterizes these contemporary digital techniques in physical education that monitor and improve physical well-being. "Pedagogy," according to Bernstein (2020), is the information, techniques, and practices that are taught by a reliable source. 'Biopedagogy', therefore, encompasses educational methods in which the human body, its functions, and health-related behaviors are the focus of intervention. 'Body pedagogies' produce and transmit information, abilities, and moral standards that characterize the ideal condition of the body, identify the desirable bodies, and outline the steps required to reach a 'optimal' body (Evans & Rich, 2021).

Children's health is greatly influenced by these pedagogies and the digital corporations who produce and disseminate the tools, applications, and resources that go along with them. This method of governing via physical education, according to Vander Schee (2024, p. 558), entails using "specific knowledge and truths about how individuals should live for the improvement of themselves and society." According to Pykett (2022), pedagogy may be viewed as a regulating activity in and of itself. As a result, prior studies in the field of physical education have seen technological innovations like performance data gathering and fitness tests as instructional instruments that can improve social order and individual well-being.

New self-quantification tools are essential to the classification, categorization, and representation of physical activity. These tools include those made for kids in physical education environments. These days, algorithms are recognized as powerful tools for deciphering activity and health data, which governs and organizes children's bodies and shapes their perception of health. In the same way that some knowledge categories are given priority in standardized tests while others are ignored (Bowker & Star, 2024, p. 6), health-tracking technologies in physical education function as sorting systems that categorize and assess physical activities, emphasizing some as desirable and others as unacceptable. These divisions have a big impact on how students learn to take care of their bodies; they're not merely bureaucratic processes.

While there are differences in the specific products and algorithms used by health-tracking devices in physical education, they are all based on common classification systems that enable the combining, comparison, and visual interpretation of health data. These technologies necessitate the integration of body and health classifications and expert knowledge into algorithmic systems and mathematical models. For example, Sqord's categorization methods and algorithms integrate a specific perspective of the child's body as flexible and adaptable. Algorithm designers "transform an external world into a world within the algorithmic machine," as Neyland (2024, p. 11) puts it. This refers to the process of converting the child's body into a model that can be calculated by the algorithmic system in self-tracking devices. These algorithms combine different viewpoints from science, physiology, medicine, and psychology to build models that categorize and depict children's bodies in ways that impose particular health standards and link physical activity to numerical values. Children's perceptions and management of their health are influenced by this categorization system, which creates the notion of "health" as defined by these algorithms.

These socio-algorithmic processes have a substantial impact on each person's perspective of themselves and their worldview, but they are social constructions rather than neutral or objective (Lupton, 2023, pp. 14–15). Children who engage in self-quantification are encouraged to see their bodies as "personal laboratories," valuing "objective" statistics and measurements above subjective, sensory sensations. As Nafus and Sherman (2024, p. 1793) point out, users interact with these algorithms not as passive recipients but as active participants negotiating between external data and internal, subjective interpretations. This approach makes the body visible as data and numbers, which can then be enhanced.

Though user involvement with these technologies is flexible, the range of available activities is limited and shaped by self-quantification algorithms. Health-tracking technology integration has the potential to uphold and extend preexisting social norms and expectations in educational settings and curriculum.

The blending of new technology innovations with public health goals, such those tackling obesity, is shaping norms and expectations around child health more and more.

Growing body-quantification-focused biopedagogies in electronic health and physical education (eHPE) indicate that kids might soon be encouraged to think of their bodies as pliable things that can be fixed. For example, apps such as Sqord encourage self-tracking by letting kids personalize and present their "PowerMe" avatars on social media. According to their website, "Everything in Sqord revolves around you and your fully customizable PowerMe. You can make it resemble you or how you wish to appear that day. Your friends will see you as you want to be seen, and you'll see them as they want to be seen" (http://www.sqord.com/).

As a result, it is becoming more accepted that the learner's body may be improved via presentation. It is implied by products such as Sqord that bodies may be trained, enhanced, and optimized. Users get knowledge about body growth, maintenance, and repair through the collection, visualization, sharing, and public monitoring of personal data (Rich & Miah, 2024, pp. 305–366). This tendency toward self-quantification is a reflection of a larger fixation with using algorithms to "tune" and "perfect" bodies. Thus, the body of the infant is positioned as something that may be enhanced and reprogrammed to conform to newly established algorithmic criteria and social norms.

Surveillance is a major issue in the research on children's self-quantification, particularly in physical education. When self-tracking gadgets are paired with advanced data analytics, they go beyond simple observation to forecast future actions and medical consequences. Self-tracking is promoted as a less intrusive kind of monitoring, in contrast to conventional covert digital surveillance carried out by organizations or governments. Users willingly give away their personal information, which is consistent with the idea of "dataveillance" (Raley, 2023).

The gamified design of health tracking, especially when promoted to kids and educational institutions, makes volunteer surveillance appealing. With the help of game-like features, apps like Sqord, Fitter Critters, and Zamzee encourage kids to be active by offering prizes and competitions. Gamification is a technique used to make daily activities more fun and motivating by offering prizes and points for positive actions. 'Pleasurable surveillance,' according to Whitson (2023), is a fun and interesting type of self-monitoring. These gadgets' proprietary algorithms, which incorporate value judgments that could favor some activities over others, make them anything than impartial.

Health tracking devices, according to Ruckenstein (2024, p. 69), make previously "unknown" aspects of bodies and lives more "detectable" and "visible." Programs such as Sqord break down individuals into data flows, visualizing activity points and using them as virtual currency to customize avatars. Through objective facts, these data-driven representations help kids comprehend their physical situations and encourage them to take better care of their health. The algorithms in question convert abstract statistics into convincing instruments for self-reform by converting biophysical data into useful insights.

The trend of dataveillance being a primary educational technique is highlighted by the incorporation of health-tracking devices into physical education. Digital analytics are already being utilized in physical education, as demonstrated by US products like Fitnessgram, and this trend is only expected to grow with the release of newer technology. Fitnessgram has an impact on how schools create physical education programs and report results, according to Gard (2024, p. 833). This trend is probably going to continue as more digital tools become available.

According to Lupton (2024, p. 9), some professors require their students to utilize digital self-tracking devices in order to track their engagement, which is referred to as "imposed self-tracking" in the context of education. This suggests that curriculum design and pedagogical approaches are being influenced by data collecting, creating a feedback loop where data analysis impacts learning environments.

The way students interact with technology is changing as a result of health-tracking devices in the classroom. Metaphors used to explain self-tracking frequently equate the body to a machine, drawing from post-humanist viewpoints that blur the line between humans and technology. The body is portrayed as a component of an integrated digital system by terms like "data factory," "dashboard for your body," and "body hacking" (Lupton, 2023, pp. 26–27). According to this perspective, the body functions as a "smart machine" inside a network of other devices, with technological means mediating and turning physical experiences into data.

According to the concept of the body as a "digital cyborg," self-tracking gadgets connect the body to a data and analytics network, forming a "corporealgorithmic" relationship. The body is viewed as a component of a dispersed information system that is encircled by "artificial skins" and technological infrastructures (Beer, 2023, p. 131). These synthetic skins are permeable, allowing data flows to be combined with motion and activity.

Students are more often connected to algorithmic models through health-tracking gadgets like Polar Active, Sqord, and Zamzee, which affects how they perceive and use their physical skills. The way people connect with their surroundings and think about themselves is affected by the changing media technologies (Hall, 2023). According to recent biopolitical theories, bodies are viewed as programmable objects that are shaped by data analysis and algorithms (Lemke, 2021; Rose & Abi-Rached, 2023). Health data processing redefines the student's body and identity as a result of biological and algorithmic elements, and it also creates tailored goals.

Utilizing personal analytics and health-tracking technology, electronic health and physical education (eHPE) offers a novel approach to biopedagogy that centers on the algorithmic control of the body. These biopedagogies reflect a focus on "tuning" and "perfecting" the body using algorithms that are common in the self-quantification movement, and they are consistent with a culture of self-optimization through numerical measures. A certain set of socially built health categories that are now included into algorithms that monitor, assess, and quantify psychological and physical activity are at the heart of self-quantification. The external world is transformed into data that can be interpreted by algorithms through this process, which converts the student's body into data that matches pre-existing health models (Neyland, 2024). These algorithms use meticulous data collecting and tracking to classify and regulate the physical states of the students.

These self-quantification tools in eHPE are justified by the idea that better control and regulation of the student's body may be achieved through quantification. The body of a kid is viewed in this paradigm as software that may be improved and optimized in accordance with algorithmic instructions. This entails forecasting the future in addition to gathering facts in real time. With the use of predictive analytics, machine learning, and computational statistics, which anticipate people's future actions and results, biopolitics is beginning to place more emphasis on future forecasts.

By metaphorically covering the quantified youngster in a "algorithmic skin"—a dynamic informational layer interacting with a complex, coded environment—these predictive technologies have the potential to have a substantial negative influence on children's health. Concerns concerning the blending of physical development with media and data flows, as well as the impact of data technology on social and personal health, are raised by the introduction of self-quantification into health and physical education.

Decision Making in Physical Education Programs

The awareness of the responsibilities and choices made by physical education (PE) teacher educators has improved due to the global expansion of PETE research (Ovens & Fletcher, 2024). These teachers' pedagogical decisions have an influence on curriculum development, as can be seen by looking at the material and instructional strategies they select (Lunenberg et al., 2022; McDonough et al., 2023). In teacher education techniques, for example, some concepts could be more frequently emphasized (Kosnik, 2022 Loughran, 2022). As a result, it is imperative that teacher educators assess what is taught, how it is taught, and why (Loughran, 2022). Studying how PE teacher educators make decisions can help to understand their priorities, the reasons behind their decisions, and how to make more deliberate and thoughtful decisions (McDonough et al., 2023). Gaining an understanding of how PE teacher educators mold PETE experiences can improve one's understanding of how teacher education operates.

Because teacher educators' decision-making is impacted by both personal and professional beliefs and judgments, it can be difficult to evaluate (Lunenberg et al., 2022). By connecting practice decisions with educational principles, research on self-study of teacher education practices (S-STEP) has attempted to capture the relationship between values and decision-making (Fletcher, 2021). To get a deeper understanding of decision-making processes, PE teacher educators have also investigated the experience of pedagogical transformation (Philpot, 2021). To record and examine turning points in the process of making educational decisions, Brandenburg et al. (2021) recommend the use of pedagogical confrontations.

According to Fletcher and Ní Chróinín (2022), meaningful experiences are prioritized while making pedagogical decisions in meaningful physical education. Meaningful PE aims to make physical education more meaningful for children by showing them how important it is and how it may improve their life. Thus, learning is both a means and an end in itself when it comes to meaningfulness. Democratic and reflective pedagogies, which influence our ideas and behaviors, are essential for creating meaningful experiences, according to Fletcher and Ní Chróinín (2022). A shared foundation for future teacher development is also provided by the pedagogical principles of Learning about Meaningful PE (LAMPE) (Ní Chróinín et al., 2023). Among these guidelines are:

Ensuring that throughout the PETE experience, meaningfulness is a clear and constant focus.

Encouraging aspiring educators to participate in meaningful ways as both students and teachers.

Gaining knowledge of the viewpoints of educators and students in order to better comprehend learner positioning.

Creating educational activities that take meaningful involvement into account.

Promoting contemplation on the significance of physical education encounters.

These ideas have been used by teacher educators to inform their choices on how much focus to place on meaningfulness in physical education (Coulter et al., 2021; Fletcher et al., 2021). According to Fletcher et al. (2020), these principles are successful in shaping and bolstering the learning of future teachers, suggesting that they provide a well-organized structure for encouraging purposeful physical education experiences.

PETE students can interact with Meaningful PE through LAMPE. Transformative pedagogies, which combine the ideas of critical pedagogy and social constructivism (Tinning, 2022), are consistent with the democratic and reflective methods found in Meaningful PE and social justice pedagogies. We have already discussed the advantages of using these ideas to enhance pre-service teachers' learning in PETE programs (Iannucci et al., 2023) in our study. In particular, individual and societal issues can be addressed by integrating meaningful PE and social justice, with democratic and reflective practices serving as a bridge between these two domains. More investigation is needed to see how teacher educators' daily decision-making incorporates meaningful physical education and social justice.

Theoretical Framework

Artificial Intelligence (AI)-driven data analytics is significantly transforming decision-making processes in various fields, including education. For Physical Education (PE) programs, the adoption of AI technologies presents opportunities to enhance decision-making efficiency and improve program outcomes. The Technology Acceptance Model (TAM), developed by Davis (1989), offers a relevant theoretical framework for exploring the impact of AI-driven data analytics in PE programs. According to TAM, the perceived usefulness and perceived ease of use of technology are crucial factors influencing its adoption and effective utilization.

Perceived usefulness is defined as the extent to which an individual believes that using a technology will improve their job performance. In PE programs, AI-driven data analytics can significantly enhance decision-making by providing detailed insights into various aspects of student performance and program effectiveness. Research by Albright and Gonzalez (2022) shows that educators who view AI tools as beneficial are more likely to incorporate them into their decision-making processes, leading to better program management and student outcomes. AI technologies enable the processing and analysis of large data sets, which can support personalized learning and more effective program adjustments. According to Voss and Patel (2023), AI tools can help educators identify trends, predict outcomes, and make evidence-based decisions that enhance overall program efficiency.

Perceived ease of use refers to how effortless a technology is perceived to be. For AI-driven data analytics to be successfully integrated into PE programs, it must be user-friendly and accessible. A study by Harper and Kim (2021) emphasizes that when AI systems are designed with intuitive interfaces and minimal technical complexity, educators are more likely to adopt and effectively use these tools. The ease of use of AI tools also affects how readily educators can incorporate them into their daily practices. A study by Kumar and Hernandez (2024) found that the adoption of AI technologies is significantly influenced by their user-friendliness and the availability of support resources, which can facilitate smoother integration into educational settings.

TAM posits that perceived usefulness and ease of use impact an individual's behavioral intention to use a technology, which then affects actual usage. For AI-driven data analytics to be effectively utilized in PE programs, it is important that educators have a positive intention to use these tools, based on their perceived benefits and ease of use. Research by Lopez and Carlson (2023) found that educators' intention to use AI tools is a significant predictor of their actual implementation in educational settings.

The application of AI-driven data analytics can enhance decision-making efficiency by providing actionable insights and data-driven recommendations. AI tools can support more accurate assessments of student performance, improve program planning, and optimize resource allocation. A study by Jensen and Lee (2022) indicates that AI-driven decision-making in education leads to more precise and timely decisions, which can positively impact program effectiveness and student success.

While TAM provides a useful framework for understanding the adoption of AI-driven data analytics, it is also important to address potential challenges such as data privacy, ethical concerns, and the need for proper training. Research by Zhang and O'Connor (2023) highlights the importance of addressing these issues to ensure the successful implementation and use of AI tools in educational environments.

The Technology Acceptance Model (TAM) offers valuable insights into the factors influencing the adoption of AI-driven data analytics in PE programs. By focusing on perceived usefulness and perceived ease of use, educators and administrators can better understand how to integrate AI technologies effectively, ultimately enhancing decision-making efficiency and improving educational outcomes.

Conceptual Framework

Figure 1 shows the research paradigm on the assessing the relationship between the athlete respondents' assessment of the AI-driven data analytics and the decision-making efficiency in the physical education programs in their institution in Wuhan Sports University. It will likewise present the correlation between artificial intelligence (AI)-driven data analytics and decision-making efficiency in physical education programs.

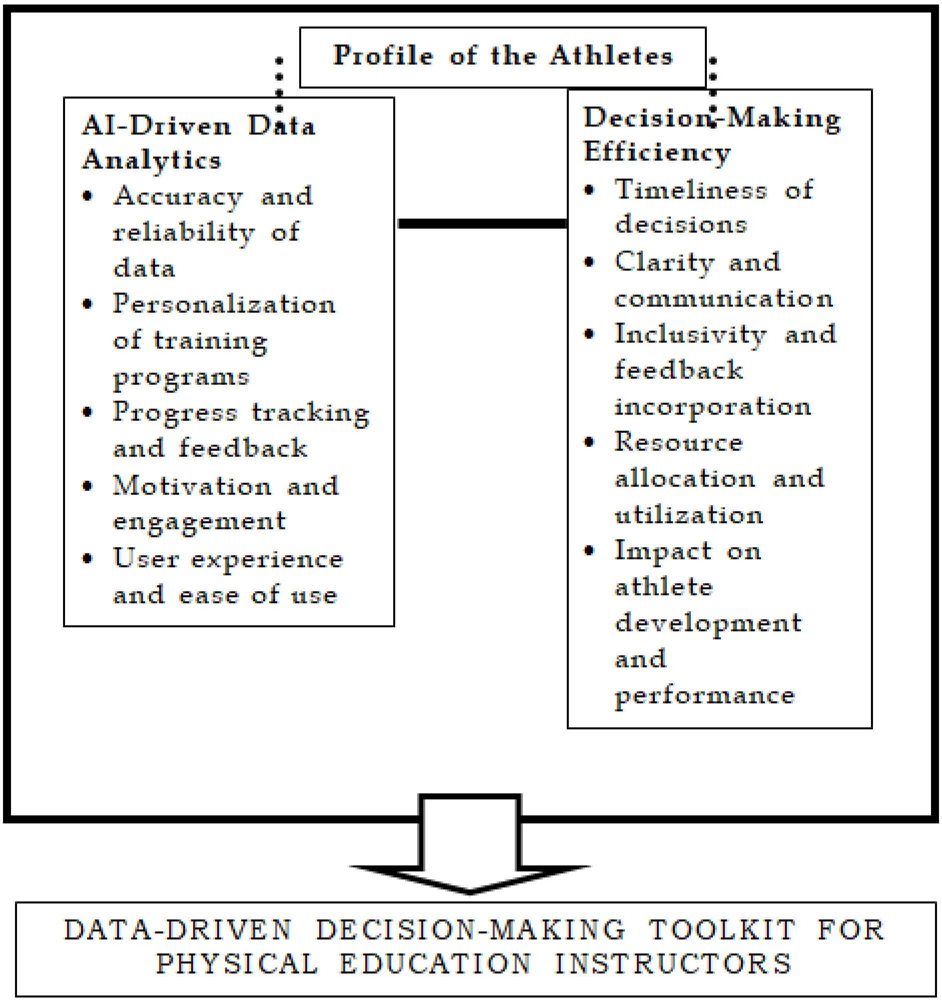

Figure 1. Research Paradigm

Figure 1 indicates the research paradigm of the study. It presents the intervening variables, specifically the athletes' demographic data. It also presents the athlete respondents' assessment of the AI-driven data analytics, and the decision-making efficiency in the physical education programs in their institution.

It shows the expected output of the study, which is the data-driven decision-making toolkit for Physical Education instructors.

Definition of Terms

AI-Enhanced Coaching. The use of artificial intelligence to support and improve coaching practices. AI-enhanced coaching provides data-driven insights, personalized feedback, and advanced analysis to optimize training and performance.

Algorithmic Optimization. The use of algorithms to enhance processes and outcomes by analyzing data and making adjustments. In physical education, algorithmic optimization can improve training efficiency, resource allocation, and decision-making.

Artificial Intelligence (AI). Technology that enables machines to perform tasks that typically require human intelligence, such as learning, problem-solving, and decision-making. In physical education programs, AI can be used to analyze data and enhance decision-making processes.

Athlete Development. The process of enhancing an athlete's skills, knowledge, and physical abilities through training, coaching, and support. Effective athlete development is informed by data analytics and AI insights.

Athlete Performance. The measurement and evaluation of an athlete's ability and achievements in their sport. Performance metrics are analyzed to assess progress, identify strengths and weaknesses, and guide improvement strategies.

Behavioral Analytics. The analysis of behavior patterns to understand and predict actions and outcomes. Behavioral analytics in physical education can reveal trends in athlete engagement, performance, and adherence to training.

Customized Training Programs. Training regimens tailored to the specific needs, abilities, and goals of individual athletes. AI-driven data analytics helps design personalized training programs based on detailed performance and health data.

Data Analytics. The systematic analysis of data to uncover patterns, correlations, and insights that can inform decision-making. In physical education, data analytics involves evaluating performance metrics, tracking progress, and improving program effectiveness.

Data Integration. The process of combining data from various sources to create a comprehensive view. In physical education, data integration involves merging performance, health, and training data to enhance analysis and decision-making.

Data-Driven Insights. Knowledge and recommendations derived from analyzing data trends and patterns. In physical education, data-driven insights inform coaching strategies, program development, and athlete support.

Decision-Making Efficiency. The ability to make effective and timely decisions based on available data and insights. Efficient decision-making in physical education programs involves using analytics to guide training strategies, resource allocation, and program adjustments.

Efficiency Metrics. Measures used to evaluate the effectiveness and productivity of processes and systems. Efficiency metrics in physical education assess how well data analytics and AI contribute to improved decision-making and program success.

Performance Metrics. Quantifiable measures used to evaluate an athlete's performance. Metrics can include physical tests, skill assessments, and competition results, and are used to track progress and guide training.

Predictive Analytics. The use of data, statistical algorithms, and machine learning techniques to identify the likelihood of future outcomes. In physical education, predictive analytics can forecast athlete performance, injury risks, and training effectiveness.

Predictive Modeling. The use of statistical techniques and machine learning to create models that predict future outcomes based on historical data. Predictive modeling helps anticipate athlete performance trends, injury risks, and program impacts.

Program Effectiveness. The success and impact of physical education programs in achieving their goals, such as improving athlete performance, increasing participation, and enhancing overall fitness.

Progress Tracking. The process of monitoring and recording advancements and achievements over time. In physical education, progress tracking helps assess improvements in athlete performance and program outcomes.

Real-Time Feedback. Immediate responses and evaluations provided during or shortly after an activity or performance. Real-time feedback helps athletes and coaches make quick adjustments and improvements.

Training Adaptability. The ability to adjust training programs and strategies based on data and feedback. Training adaptability ensures that programs remain effective and responsive to the evolving needs of athletes.

User Experience. The overall experience and satisfaction of individuals interacting with a system or program. In the context of AI-driven data analytics, user experience includes the ease of use, accessibility, and responsiveness of the technology for educators and athletes.

Visualization Tools. Software and techniques used to present data in graphical formats, such as charts and graphs. Visualization tools help educators and coaches interpret data more easily and make informed decisions.

Methodology

Research Design

The research utilizes a descriptive, comparative, and correlational technique that is characterized by its accurate definitions, thorough recording, in-depth analysis, and sophisticated comprehension of contextual interactions. Martin and Dubois (2024) state that descriptive research aims to methodically identify and investigate the essential features, behaviors, and traits of phenomena in their natural environments. The main objective is to create thorough profiles of certain entities or to comprehend the current situation better to provide the groundwork for future study.

Building on the results of Martin and Dubois (2024), descriptive research is essential to the social sciences and psychology because it offers a comprehensive knowledge of natural patterns and behaviors. It makes it easier to gather precise and impartial information on the beliefs, actions, and characteristics of target audiences, which produces insightful information about the workings of society.

Additionally, Fortin and Rousseau (2023) emphasize how important it is to use comparative techniques in order to pinpoint the main variables influencing events in various populations or environments. They contend that by revealing putative causal links between variables, correlational analysis is essential for boosting the explanatory power of study designs. Correlational analysis will be used in this study to investigate the relationships between particular demographic traits and pertinent attitudes or behaviors related to the research issue, which will help establish theoretical frameworks and practical intervention techniques.

An effective foundation for examining the intricate relationships between variables and settings is provided by the descriptive-comparative-correlational technique used in this investigation. This technique combines extensive descriptions, comparative analysis, and correlational insights by merging the methodological ideas from Fortin and Rousseau (2023) with the essential concepts described by Martin and Dubois (2024). This rigorous technique improves the findings' validity and depth and lays a solid platform for further study and real-world applications in related domains.

This study aims to investigate the athletes' assessment of AI-driven data analytics and the decision-making efficiency and its relationship to the decision-making efficiency in the physical education programs in their institution.

This research approach allows the researcher to numerically analyze, compare, and correlate the relationships amongst the dependent variables included in the study.

By utilizing this approach, the researcher will be able to find any significant difference or relationship in the athlete respondents' assessment of the AI-driven data analytics in the physical education programs in their institution and their demographic data such as sex, age, year level, sports focused and number of years as athletes. Also, the researcher will be able to find any significant difference or relationship in the athletes' assessment of the decision-making efficiency in the physical education programs in their institution and their demographic data such as sex, age, year level, sports focused, and number of years as athletes. The athletes' assessment of the AI-driven data analytics and the decision-making efficiency in the physical education programs in their institution will then be correlated.

All the above discussions on the descriptive research method will suit the nature of research that this present study would do; hence this method will be adopted.

Research Locale

The study will be done in a selected sports university in Wuhan City Hubei Province, China – Wuhan Sports University. Wuhan Sports University, referred to as "Wuti", located in Wuhan City, Hubei Province, is a full-time ordinary institution of higher learning jointly established by the General Administration of Sports of the People's Republic of China and the People's Government of Hubei Province, and is mainly managed by Hubei Province.

Wuhan Institute of Physical Education, formerly known as Central South Institute of Physical Education, is one of the first batch of independent full-time ordinary higher sports colleges in the People's Republic of China, founded in Nanchang City, Jiangxi Province in 1953, moved to Wuhan City, Hubei Province in 1955, renamed Wuhan Institute of Physical Education in 1956, directly under the State General Administration of Sports, and jointly established by the State General Administration of Sports and Hubei Provincial People's Government in 2001. The school has a tertiary directly affiliated hospital and a tertiary affiliated hospital. The school adheres to the school motto of "public courage, sincerity and perseverance, learning to think critically and act", adheres to the school-running philosophy of "integrating sports, science and technology, and humanities education, and integrating morality, culture and professional quality", and has cultivated and delivered more than 150,000 outstanding talents for the country over the past 70 years.

As of January 2024, the school has East Lake (Zhuodaoquan) Campus, Zanglong Island Campus, East Lake High-tech Zone (Baolu) and Wudangshan Campus, covering an area of 1,820 acres; There are 14 secondary colleges with 25 undergraduate majors; There are 1 post-doctoral research station, 1 first-level discipline doctoral degree authorization point, 6 first-level discipline master's degree authorization points, and 5 professional master's degree authorization points; There are more than 900 faculty members, including more than 14,000 undergraduates, master's and doctoral students, and international students.

Sampling Technique

The respondents of the study will be the athletes from Wuhan Sports University. In selecting the athlete respondents, stratified random sampling technique will be used among the athlete respondents.

Stratified random sampling is a method of sampling that involves the division of a population into smaller groups known as strata. In stratified purposive sampling, or stratification, the strata are formed based on members' shared attributes or characteristics. For the computed needed respondents, of the __ athletes from ______, using 5% of margin of error, () athletes will be randomly selected as the respondents.

Research Instrument

In gathering the needed data, the researcher will make researcher-made questionnaires on the athletes' assessment of the AI-driven data analytics, and the decision-making efficiency in the physical education programs in their institution.

The researcher will use face to face or onsite in administering this questionnaire.

The questionnaire will be composed of the following parts.

Part 1 – This section determines the demographic profile of the martial arts athlete respondents.

Part 2 – This section determines the AI-driven analytics in the physical education programs in the athlete respondents' institution

Part 3 – This section identifies the decision-making efficiency in the physical education programs in the athlete respondents' institution

AI-Driven Analytics in the Physical Education Programs

Scale	Verbal Interpretation
3.51 - 4.00	**Very Effective** *If the statements are very true of their program, 76%-100% level of effectivity.*
2.51 -3.50	**Effective** *If the statements are true of their program, 51%-75% level of effectivity.*
1.51 -2.50	**Slightly Effective** *If the statements are slightly true of their program, 26%-50% level of effectivity.*
1.00-1.50	**Not Effective** *If the statements are not true of their program, 1%-25% level of effectivity.*

Decision-Making Efficiency in the Physical Education Programs

Scale	Verbal Interpretation
3.51 - 4.00	**Very Efficient** *If the statements are very true of their program, 76%-100% level of efficiency.*

2.51 -3.50 **Efficient**

If the statements are true of their program, 51%-75% level of efficiency.

1.51 -2.50 **Slightly Efficient**

If the statements are slightly true of their program, 26%-50% level of efficiency.

1.00-1.50 **Not Efficient**

If the statements are not true of their program, 1%-25% level of efficiency.

The adapted questionnaire and the researcher-made questionnaire will be subjected to content validation of the experts who are knowledgeable in the field of research. The suggestions of the experts will be made integral in the instrument.

The same instrument will be submitted for face validation with at least five experts. The questionnaires will be pilot tested to measure reliability. The pilot testing will be computed using Cronbach's Alpha through the Statistical Package of Social Science (SPSS). The researcher welcomes the suggestions of the experts and will make necessary revisions to construct the said instruments valid.

Data Gathering Procedure

The researcher will get permission from the office of the principal of Wuhan Sports University.

When the permission is approved, the researcher will ask permission from the coaches by distributing a letter of consent form to the athlete respondents, which will be signed by them and will be returned to the researcher.

After, the purpose of the study and instructions on how the items on the survey should be answered will be explained to the athlete respondents. Then, the survey will be administered using the face to face and they will be given enough time to answer the survey.

After completing the survey, the researcher will collect the questionnaires from the athlete respondents.

The data will be gathered, tallied, and processed with Statistical Package for Social Science (SPSS). The processed data will be interpreted and analyzed, and the results will be used to propose a data-driven decision-making toolkit for Physical Education instructors

Finally, the interpretation and analysis of data will be done. Summary of findings, conclusions, and recommendations will be formulated.

Statistical Treatment of the Data

The responses to the survey questionnaire will be tallied using the SPSS, and then they will be tabulated and organized accordingly. The data will be presented, analyzed, and interpreted using frequency, percentage, mean, standard deviation, independent samples t-test, one-way ANOVA, and Pearson's r correlation.

For research question no. 1, descriptive statistics such as frequency counts and percentages will be used to treat responses in the demographic profile of the athlete respondents.

For research question nos. 2 and 4, weighted means will be utilized to treat the assessment of the athlete respondents of the AI-driven data analytics in physical education programs in terms of accuracy and reliability of data, personalization of training programs, progress tracking and feedback, motivation and engagement, and user experience and ease of use.

Weighted means will also be used to compute for the assessment of the athlete respondents of the decision-making efficiency in the physical education programs in their institution in terms of timeliness of decisions, clarity and communication, inclusivity and feedback incorporation, resource allocation and utilization, and impact on athlete development and performance.

The following will be used to interpret the WM of the athletes' responses:

Mean Range	**Verbal Description**
3.51 - 4.00	Very True of Our Program
2.51 - 3.50	True of Our Program
1.51 - 2.50	Slightly True of Our Program
1.00 - 1.50	Not True of Our Program

For research question nos. 3 and 5, one way ANOVA with post-hoc analysis (Scheffe) will be used to find out the significant difference in the assessment of the athlete respondents of the AI-driven data analytics and the decision-making efficiency in the physical education programs in their institution.

For research question no. 6, Pearson's r correlation analysis will be utilized to determine the significant relationship between AI-driven data analytics and the decision-making efficiency in the physical education programs in athlete respondents' institution.

Ethical Considerations

The researcher will constructively consider and carefully follow the ethical considerations that must be met to protect the rights of all the respondents. The following are the ethical considerations:

1. Conflict of Interest

The researcher of this study ensured that there would be no conflict of interest. The researcher needed to elaborate and clearly state the purpose of this research and study to the chosen respondents. It is also a must that the researcher must stick to the purpose of gathering personal information and data. All gathered data must not be used for any form of exploitation against the respondents. The researcher must stick to the objective of the research and its purpose.

2. Privacy and Confidentiality

Before conducting this research, the respondents will be assured that whatever information would be gathered would be confidential, and the survey results cannot be given to anyone aside from the researcher himself and the person who answered the survey – questionnaire. The researcher must not mention the respondents' names in presenting the data gathered to protect their privacy. The identity of the respondents would remain anonymous or free from any clues and suggestions that would lead others to connect or relate with the respondents.

3. Informed Consent Process

Before conducting the survey questionnaire, the researcher will secure a consent form that gives confirmation and consent from the respondents that they understand the purpose and objective of this study and agreed that the data gathered would strengthen the researcher's study. The researcher will make sure that she explains thoroughly and clearly everything to the respondents without any deception. The process and the possible risks in participating in this study will also be discussed.

4. Recruitment

The respondents of this study will be the physical education teachers. The respondents will be free to exercise their rights to disagree and agree in participating in this study. The respondents will not be forced to participate and will be given the freedom to refuse at any point in time.

5.Risk

The researcher of this study will ensure that there would be no risk in participating in this study. The respondents will ensure that whatever data and information would be gathered would not harm respondents' life and name. The respondents had all the rights to freely stop the conduct of questions at any given time if they felt harassed, questions were too personal and or violated.

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Appendix A

ARTIFICIAL INTELLIGENCE (AI)-DRIVEN DATA ANALYTICS AND DECISION-MAKING EFFICIENCY IN PHYSICAL EDUCATION PROGRAMS

ATHLETES' QUESTIONNAIRE

Part l. Profile of the athlete respondents in terms of:

Name ______________________________________

1.2 Sex: (   ) Male   (   ) Female

1.3. Age: (   ) less than 15 yrs. old   (   ) 18 yrs. old
(   ) 16 yrs. old   (   ) more than 18 yrs. old
(   ) 17 yrs. old

1.4. Year Level: (   ) Year 1
(   ) Year 2
(   ) Year 3
(   ) Year 4

1.5 Focused Sports: (   )
(   )
(   )
(   )
(   )
(   )

1.4 Number of Years as an Athlete: (   )
(   )
(   )
(   )
(   )

Part II. AI-Driven Analytics in Physical Education (PE) Programs

Direction: For each statement below, please assess the AI-driven analytics in your PE programs in the following areas by indicating the extent to which each statement is true of you. Rate the AI-driven analytics in your PE programs on a scale from 1 to 4, where:

Rate	**Verbal Interpretation**
4	Very True of Our Program

3 True of Our Program
2 Slightly True of Our Program
1 Not True of Our Program

Indicators	**(4)**	**(3)**	**(2)**	**(1)**
Accuracy and Reliability of Data				
The data provided by the AI system is consistently accurate.				
The AI system provides reliable measurements of my physical performance.				
I trust the data analytics to reflect my true abilities.				
The data from the AI system is free from significant errors.				
I find the AI-generated data to be dependable for assessing my progress.				
The AI system accurately tracks various aspects of my training.				
The results from the AI system are consistent with my physical observations.				
The data analytics system produces reliable results over time.				
I am confident in the accuracy of the AI system's feedback.				
The AI data analytics are precise in recording my workout metrics.				
Personalization of Training Programs				
The AI system tailors training programs to my specific needs.				
My training plan is adjusted based on AI insights into my performance.				
The AI system customizes workouts based on my individual strengths and weaknesses.				
The training recommendations from the AI are personalized and relevant to my goals.				
I receive individualized feedback from the AI system on my training.				
The AI system adapts my training program as I progress.				
The AI-driven program offers exercises suited to my unique fitness level.				
My training regimen is modified according to the AI's recommendations.				
The AI system provides personalized tips for				

improving my performance.				
The training suggestions from the AI reflect my personal preferences and needs.				
Progress Tracking and Feedback				
The AI system effectively tracks my progress over time.				
I receive regular updates on my training progress from the AI system.				
The feedback provided by the AI system helps me understand my performance improvements.				
The AI system offers detailed reports on my training history.				
I get actionable feedback from the AI system regarding my progress.				
The AI analytics provide insights into my performance trends.				
The system tracks and highlights areas of improvement in my training.				
The AI system monitors my progress accurately across different workouts.				
The feedback I receive from the AI is timely and helpful.				
I can easily review my progress through the AI system's analytics.				
Motivation and Engagement				
The AI system enhances my motivation to train.				
The feedback from the AI system keeps me engaged in my training program.				
I feel more driven to achieve my goals due to the AI system's encouragement.				
The AI system provides motivational insights that inspire me to work harder.				
I find the interactive elements of the AI system engaging.				
The AI system's notifications and feedback boost my training enthusiasm.				
The AI system helps me set and achieve personal milestones, increasing my motivation.				
The gamification aspects of the AI system make training more exciting.				
I am more committed to my training program				

because of the AI system's support.				
The AI system's progress tracking fuels my desire to improve.				
User Experience and Ease of Use				
The AI system is easy to navigate and use.				
I find the interface of the AI system user-friendly.				
The AI system integrates smoothly with my existing training tools.				
The setup and configuration of the AI system are straightforward.				
I can quickly access the information I need from the AI system.				
The AI system provides a seamless user experience.				
I find it easy to input and track my training data through the AI system.				
The AI system's features are intuitive and simple to use.				
I encounter minimal technical issues while using the AI system.				
The AI system offers clear instructions for using its features.				

Part III. Decision-Making Efficiency in the Physical Education (PE) Programs

Direction: For each statement below, please assess the decision-making efficiency in the PE programs of your institution in the following areas by indicating the extent to which each statement is true of you. Rate the decision-making efficiency in the PE programs of your institution on a scale from 1 to 4, where:

Rate	Verbal Interpretation
4	Very True of Our Program
3	True of Our Program
2	Slightly True of Our Program
1	Not True of Our Program

Indicators	(4)	(3)	(2)	(1)
Timeliness of Decisions				
Decisions in our physical education program are made promptly.				

The program effectively addresses issues in a timely manner.				
There is minimal delay in decision-making processes within our program.				
Urgent matters are handled quickly by the program administrators.				
Decisions related to scheduling and events are made with sufficient lead time.				
The program responds swiftly to unexpected changes or problems.				
The pace of decision-making in the program supports effective planning.				
Timely decisions are made regarding resource allocation and usage.				
Program decisions are timely enough to support optimal athlete performance.				
The decision-making process avoids unnecessary delays.				
Clarity and Communication				
Decisions within the program are clearly communicated to athletes.				
The reasons behind decisions are explained effectively.				
There is transparent communication about changes in the program.				
Athletes are kept informed about decision outcomes and their implications.				
Communication regarding program decisions is consistent and clear.				
The program provides clear instructions and guidelines following decisions.				
Decision-makers are accessible for clarifying any uncertainties.				
The program uses multiple channels to ensure effective communication.				
Athletes receive timely updates on decisions that affect their training.				
Communication about decisions is straightforward and easy to understand.				
Inclusivity and Feedback Incorporation				
The program considers athlete feedback when making decisions.				
Athletes have opportunities to contribute to				

decision-making processes.				
Feedback from athletes is actively sought and valued by the program.				
The decision-making process is inclusive of diverse athlete perspectives.				
The program incorporates athlete suggestions into decisions where applicable.				
There are structured methods for athletes to provide feedback on decisions.				
Decisions are made with consideration of the needs and concerns of all athletes.				
The program adapts decisions based on athlete input and feedback.				
Athletes feel their opinions are considered in the decision-making process.				
The program regularly reviews feedback to improve decision-making practices.				
Resource Allocation and Utilization				
Resources are allocated efficiently to meet the needs of athletes.				
The program utilizes available resources effectively to enhance training.				
Decisions regarding resource allocation are made with the athletes' best interests in mind.				
There is a clear strategy for resource distribution within the program.				
The program makes the best use of its facilities and equipment.				
Resource allocation supports both individual and team development.				
The program ensures equitable distribution of resources among athletes.				
Decisions on resource use are made with consideration of their impact on athlete performance.				
Resources are allocated in a way that maximizes their effectiveness.				
The program effectively manages its budget to support athlete needs.				
Impact on Athlete Development and Performance				
Decision-making processes positively impact athlete development.				
Program decisions contribute to improved				

athlete performance.				
The program's decisions support athletes' personal and athletic growth.				
Decisions are made with a focus on enhancing overall athlete performance.				
The outcomes of decisions are reflected in athletes' progress and achievements.				
The program's approach to decision-making helps athletes reach their potential.				
Decisions made within the program are aligned with athletes' long-term goals.				
The program evaluates the impact of decisions on athlete development regularly.				
Decision-making supports both the short-term and long-term success of athletes.				
The program's decisions have a positive effect on athletes' competitive performance.				