Chapter Two: Literature Review

2.1. Introduction

Final year student projects are a critical component of higher education, especially in science and engineering programs. These projects often require matching each student with a suitable project topic and supervisor a process traditionally done by hand. Manual project allocation can be time consuming and prone to issues such as unfair assignments or mismatches between student interests and project topics. Such mismatches may lead to poor student-supervisor relationships and lower student satisfaction. In recent years, automated student project allocation systems have emerged to streamline this matching process. These systems use algorithms to assign students to projects based on various criteria like student preferences, project availability, and staff workload. Automating allocation promises to improve fairness and efficiency, ensuring more students get projects aligned with their interests and more equitable distribution of supervision load (Hussain et al., 2019).

Alongside allocation, verification systems have gained importance in academic settings. Verification in this context refers to authenticating student identity and validating the integrity of project work or credentials. With more processes moving online accelerated by factors like the COVID-19 pandemic (Khurwolah & Chuttur, 2020) institutions seek robust ways to ensure the right student is undertaking the right project and that records (like project submissions or certificates) are authentic. Technologies such as blockchain and biometrics are increasingly explored to address these needs. Blockchain can provide tamper-proof records of project allocations or academic credentials, making verification quicker and trustless (Rustemi et al., 2023). Biometric authentication (e.g. fingerprint or facial recognition) offers a reliable way to confirm a student’s identity when accessing systems or submitting work (Hernandez-de-Menendez et al., 2021). Both approaches aim to uphold academic integrity in an automated system.

Objective of the Literature Review: This literature review critically examines key studies from the last decade (approximately 2015–2024) on automated student project allocation and verification systems. The goal is to understand the state of the art and how these studies support or challenge the thesis that automating project allocation (with integrated verification) improves the educational process. We organize the discussion into thematic areas from allocation methodologies and the use of AI, to verification mechanisms like blockchain/biometrics, to challenges and ethical considerations. By synthesizing findings and trends, we identify gaps in existing research and clarify how our research will contribute to filling those gaps. This structured review lays the groundwork for the thesis by highlighting what is known, what remains problematic, and why the topic of automated project allocation and verification is important for modern higher education administration.

2.2. Conceptual Framework

Defining Project Allocation: Student project allocation is essentially a resource matching problem where students, project topics, and supervisors must be matched under various constraints (Hussain et al., 2019). Each student typically needs a unique project (or a seat in a project group), and each faculty member can supervise only a limited number of projects creating a classic allocation challenge. Often, both students and supervisors have preferences: students may rank project topics or preferred supervisors, and lecturers may have preferences for certain projects or even for particular students. The Student Project Allocation (SPA) problem has been formally studied in algorithm design as a variant of the stable matching problem (Manlove & O’Malley, 2008). In SPA, we seek an assignment of students to projects (and possibly to supervisors) that satisfies capacity constraints (e.g. each project or supervisor has a max number of students) and, ideally, optimizes preference satisfaction or stability. A stable matching (in this context) would mean no student-project-supervisor trio would all prefer to be matched differently outside the given allocation. However, because students and projects often have one-sided or two-sided preferences and complex constraints, achieving a perfect stable match is difficult. Some formulations of the problem are NP-hard, requiring heuristic or approximation methods (Salami & Mamman, 2016).

In practical terms, universities have approached project allocation in several ways. Common models include:

1. Students select from available projects e.g. projects are advertised and students apply or list preferences
2. Bilateral preference matching: both students rank projects and supervisors rank students, and an algorithm attempts to find an optimal matching
3. Student-proposed projects: students propose their own project ideas which are then approved and matched with supervisors (often combined with either of the above models)
4. Hybrid or multi-phase methods e.g. initial round of student choice followed by manual adjustment or negotiation between students and supervisors (Kazakov, 2018).

Each model has theoretical underpinnings: for instance, model (ii) relates to stable matching theory, and model (iii) leans on student initiative and supervisor vetting rather than algorithmic matching (Knight & Botting, 2016).

Defining Verification in This Context: In the context of student projects, verification refers to confirming authenticity and compliance in the allocation process and outcomes. This concept has two main aspects:

1. Identity Verification: Ensuring the person participating in or submitting a project is indeed the authorized student. This need has grown with online project work and remote submissions. Biometric authentication technologies provide a solution here. For example, fingerprint or facial recognition systems can authenticate students when they log into project portals or during online project presentations. Research in educational technology shows biometrics can reliably verify student identities, thereby preventing impersonation or cheating in online environments. A 2021 review by Hernandez-de-Menendez et al. Found that biometric applications in education including fingerprint attendance systems and facial recognition are increasingly adopted to enhance security and trust in student monitoring (Hernandez-de-Menendez et al., 2021). These systems build on theories of authentication and pattern recognition, ensuring that only the right individuals access certain academic resources or receive credit.
2. Outcome Verification: Ensuring that allocated projects and their results are legitimate and tamper-proof. This includes verification of project selections, submissions, and credentials. Blockchain technology provides a theoretical foundation for this through its decentralized ledger and cryptographic trust model. In essence, a blockchain is a distributed database that records transactions (in this case, records like “Student X was assigned Project Y” or “Student X submitted Project Y on date Z”) in an immutable, tamper-evident way. The theoretical appeal is that once a project allocation or completion record is on the blockchain, it cannot be altered without detection, ensuring integrity. For example, Rustemi et al. (2023) note that blockchain-issued academic certificates can drastically reduce fraud by providing unchangeable digital credentials that anyone can verify independently. In project allocation systems, similar ideas could be used to verify that a student’s project assignment and final outcome have not been maliciously changed and that the student indeed completed the work. Smart contracts (self-executing code on blockchain) could even automate certain verifications, like only awarding a “project completed” credential when a supervisor and an evaluator both sign off digitally (Zhang et al., 2018).

2.3. Theoretical Framework

Theoretical Foundations and Models: Drawing from these definitions, our conceptual framework sees automated project allocation as an optimization and matching problem, whereas verification systems draw from security and trust models.

Matching and Optimization Theory: Many allocation systems are underpinned by operations research and algorithm design principles. Stable matching theory (Gale-Shapley algorithms and their extensions) has been a cornerstone, ensuring no blocking pairs of student-project want to deviate. Linear programming and network flow models have also been used to find optimal allocations under constraints (Calvo-Serrano et al., 2017). For instance, Calvo-Serrano and colleagues formulated project allocation as a linear assignment problem optimizing for overall satisfaction while respecting workload limits, solving it using integer programming. Evolutionary algorithms (genetic algorithms, etc.) and multi-criteria decision methods provide heuristic frameworks when exact solutions are infeasible (Salami & Mamman, 2016; Soares et al., 2023). These algorithms are grounded in AI and machine learning theory to search large solution spaces for near-optimal matches.

Security and Authentication Theory: Verification systems rest on cryptographic and biometric theories. Public key cryptography and distributed consensus (the basis of blockchain) ensure data integrity and non-repudiation. Theoretical models like the CAP theorem (trade-offs in distributed systems) and consensus algorithms (e.g., proof-of-work, proof-of-authority) inform how blockchain-based academic records can be managed in practice (Sharples & Domingue, 2016). Biometric verification relies on pattern recognition algorithms and physiological/behavioural feature uniqueness underpinned by statistical decision theory (e.g., computing match probabilities, false accept/reject rates). The concept of liveness detection in biometrics (to ensure the input is from a live person, not a spoof) is grounded in signal processing theory and is crucial when using face or fingerprint ID for student verification in high-stakes scenarios like remote exams or project defences.

In summary, the conceptual framework for this topic integrates algorithms for optimal matching (to allocate projects fairly and efficiently) with technologies for robust verification (to ensure the integrity of the allocation process and its outcomes). With these definitions and theoretical bases established, we can now examine how recent research has implemented and extended these concepts in practice.

Reviewing Existing Methodologies and Technologies for Project Allocation

Researchers and universities have experimented with a variety of methodologies to automate the project assignment process. Traditional manual allocation often involving faculty committees painstakingly pairing students with project topics is increasingly seen as inefficient and prone to suboptimal outcomes. Over the past decade, numerous studies propose systems and algorithms to improve on this.

Here we review key methodologies:

1. Preference-Based Matching Algorithms: A dominant theme is algorithms that account for preferences of students (and sometimes supervisors). Manlove & O’Malley (2008) pioneered an algorithm for SPA where students rank projects and projects have quotas. Building on that, Iwama et al. (2012) improved approximation bounds for SPA with preference lists, reflecting ongoing efforts to achieve stable or near-stable matchings. Moussa and El-Atta (2011) introduced a model allowing lecturers to express preferences over specific student-project pairs, increasing the realism of the preference structure. In practice, these algorithms aim to maximize satisfaction. For example, if both a student and a supervisor highly prefer to work together on a given project, the algorithm will try to honour that to avoid an unstable pairing. Preference-based methods are widely considered fairer than random or first-come approaches, because they systematically account for what stakeholders want. However, as Kazakov (2018) observed, purely preference-driven allocation can become complex and may still result in some students getting none of their choices if not carefully managed. His proposed three-phase method (essentially, iterative allocation with preference adjustment) reduced the number of randomly allocated projects, highlighting the need to blend automation with practical constraints to avoid “leftover” assignments.
2. Heuristic and Evolutionary Algorithms: Given that the allocation problem can be computationally hard, heuristic approaches like genetic algorithms (GA’s) and simulated annealing have been applied. Salami and Mamman (2016) present a genetic algorithm for allocating project supervisors to students that respects student supervisor preferences and capacity limits. Their GA encodes potential allocations as chromosomes and evolves them to maximize an objective (e.g., number of satisfied top choices). The results were promising: the GA found high-quality allocations that even compared favourably to an optimal integer programming solution, and it had the advantage of generating multiple good solutions for administrators to choose from. This is useful because in practice a department might want to review a few alternative allocations rather than blindly accept one computed outcome. Other heuristic techniques include fuzzy logic and ant colony algorithms (Srinivasan & Rachmawati, 2008), which can handle the uncertainty in preferences by not requiring strict rank ordering but fuzzy satisfaction levels. A notable recent approach is by Soares et al. (2023), who combined AHP (Analytic Hierarchy Process) and SAW (Simple Additive Weighting) to determine optimal supervisor assignments. Their system evaluates numerous criteria (education level, research area match, supervisory experience, etc.) to score and rank potential supervisor-student pairings. By using AHP to weight criteria and SAW to rank alternatives, they achieved a more nuanced matching that a simple one-criterion sort would miss. This multi-criteria decision approach is particularly relevant in contexts where a “fit” between student and project is not just preference-based but depends on multiple factors (skill alignment, project difficulty, etc.).
3. Optimization via Mathematical Programming: Some studies formulate project allocation as a formal optimization problem. For instance, Calvo-Serrano et al. (2017) describe a mathematical programming model to optimally allocate students’ projects to academics in large cohorts. They treated it as an assignment problem with the objective of maximizing overall preference satisfaction while imposing constraints like balanced faculty loads. Using integer linear programming (ILP), they could find an optimal assignment for cohorts of significant size, demonstrating that exact solutions are feasible with modern solvers if the problem is formulated smartly. Similarly, Yong and Salleh (2024) applied a linear programming approach in a case study at University Brunei Darussalam, aiming to balance student preferences, staff workload, and project quality. Their model produced an “optimal and fair project allocation” in that context, suggesting that operations research techniques can effectively handle allocation when provided with good data (Yong & Salleh, 2024). The drawback is that the ILP models might become intractable if the number of students and projects is very large or if too many complex constraints (non-linear preferences, etc.) are included. In practice, a combination of optimization for the core problem and heuristics for fine-tuning tends to work well.
4. Web-Based Allocation Systems: Beyond algorithms, technological implementations have been crucial. Several papers focus on developing online platforms that implement these matching algorithms and provide user-friendly interfaces for students and staff. For example, Abdulkareem et al. (2013) designed a university portal specifically for managing final-year project allocation. Their system allowed students to submit project choices online and enabled staff to manage and view allocations in one place, replacing paper-based processes. More recently, Ismail et al. (2017) built an online project evaluation and supervision system called oPENs, which not only allocates projects but also manages the proposal development process. Such systems typically incorporate a database of projects, student profiles, and a matching engine under the hood. They bring practical considerations to the forefront like ensuring the system can handle concurrent users, secure logins, and updates to project lists. The University of Mauritius case studied by Khurwolah and Chuttur (2020) is illustrative: they gathered requirements for an online allocation system because their manual approach was fraught with issues and delays. By adopting an online system, they hoped to streamline the process and adapt to remote needs (especially in light of the pandemic). One interesting outcome of their work was a recommended workflow for allocation, which can be seen as a codification of best practices (e.g., how to collect student preferences, deadlines for each phase, and notifications). This indicates that technology and methodology go hand-in-hand a good algorithm still needs a well-designed system around it to be effective in a real institutional setting.

In summary, existing methodologies range from discrete algorithms grounded in theory (stable matching, ILP, GA, etc.) to comprehensive systems that integrate those algorithms into usable software. The trend over the last decade is clearly toward automation: as Hussain et al. (2019) observe, many universities now employ computer-assisted allocation to handle growing student numbers, which alleviates the tedium and stress of manual assignment and often yields better matches. Each approach has its strengths e.g., ILP ensures optimality, GA offers flexibility, multi-criteria methods capture rich factors and weaknesses e.g., potential complexity, need for careful tuning, or requirement of high-quality input data. These trade-offs are actively discussed in the literature as researchers refine the balance between algorithmic sophistication and practical usability.

AI, Machine Learning, and Automation in Allocation Systems

Artificial intelligence (AI) and machine learning (ML) techniques have increasingly been applied to student-project allocation problems, reflecting a broader trend of using AI to enhance decision-making in education. While some of the heuristic methods mentioned above (genetic algorithms, fuzzy logic) are part of the AI family, newer research is explicitly leveraging machine learning to improve how preferences are elicited and satisfied in allocation.

One cutting-edge example is the use of machine learning to predict or refine student preferences. Soumalias et al. (2024) argue that one major issue in allocation is that students may not express their true or best preferences effectively they can misunderstand options or the implication of ranking. To tackle this, they developed a “Machine Learning-powered Course Match” system (applied in a course allocation context, but conceptually similar to project allocation). Their system uses an AI module to interactively query students (asking tailored pairwise comparisons between projects) to learn their preference model more accurately. The outcome was significant: in simulations with real data, the ML-powered approach increased the average student satisfaction (utility) by around 7–11% and the minimum satisfaction (worst-case student) by 17–29% compared to the traditional mechanism. This demonstrates how AI can find better allocations not by changing the matching algorithm per se, but by improving the quality of input preferences – effectively mitigating human errors in preference reporting. It supports the thesis that automation with intelligent components can outperform purely manual or static methods in terms of fairness and efficiency. Another area is prediction and recommendation., some research explores whether machine learning models can predict which project a student might excel in or enjoy, based on their academic history or interests. While direct studies on this are limited, analogous systems exist (for example, recommender systems for student elective choices or AI advising tools). The idea would be to use data grades, skills, past projects, etc. to suggest optimal matches even before the student explicitly ranks options. Although we did not find a prominent study in the last decade that fully realizes this for project allocation, it is an emerging trend in discourse. The groundwork can be seen in systems like the one by Aderanti et al. (2016), where students and supervisors input their research interest areas into the system. While their implementation used a straightforward matching algorithm, one could envision layering an AI that learns from previous years’ allocation outcomes (e.g., which matches led to successful projects) to inform future matches.

Automation broadly is no longer just about running an algorithm once; it’s about an end-to-end process that may involve AI at multiple stages. For example, an automated allocation system might automatically validate the data (ensuring students only select eligible projects, etc.), use an algorithm to assign projects, automatically notify students of their allocation. Adjust allocations in real-time if someone drops out or a new project is added (dynamic reallocation). Here, AI can help by quickly re-optimizing or by forecasting which allocations are at risk (say if a student is likely to drop out, an AI might predict that and keep a backup assignment ready). It is also worth noting the use of multi-agent systems and AI fairness frameworks. As the allocation problem inherently involves multiple stakeholders with possibly conflicting interests, researchers sometimes model it as a multi-agent system where each student and supervisor can be seen as an agent. AI techniques from game theory (like mechanism design) ensure that the system incentives truthful preference reporting and fair outcomes. Soumalias et al. (2024) above touches on mechanism design their ML-based elicitation is essentially a more incentive-compatible way to get preferences. We also see work focusing on fairness, ensuring the algorithm doesn’t inadvertently favour certain students. For instance, a naive algorithm might always give priority to top-GPA students for popular projects, leaving others consistently with lower choices. AI can be used to introduce fairness constraints (e.g., “maximize the number of students who get one of their top 3 choices” rather than purely maximizing average satisfaction). In practice, one of the programs reviewed by Hussain et al. (2019) did exactly that they used a matching algorithm with conditions to ensure, for example, that as many students as possible got their first choice, and to minimize the number getting their last choice. Such rules can be encoded and balanced using AI optimization methods.

In summary, AI and ML are adding intelligence to automated allocation systems. They not only crunch numbers faster than humans but also learn patterns and preferences to continually improve the quality of matches. This supports our thesis by showing that automated systems, especially those augmented with learning capabilities, can achieve outcomes (in terms of student-project fit and satisfaction) that manual or non-learning systems likely could not. At the same time, these advanced systems introduce new challenges particularly around trust (stakeholders trusting an AI’s decision) and complexity. We will discuss those later, but the studies so far suggest that carefully applied AI can greatly benefit the allocation process, making it more responsive and personalized without sacrificing fairness.

Verification and Authentication Mechanisms (e.g., Blockchain, Biometrics)

As project allocation systems become digital and automated, ensuring the security and authenticity of the process has become paramount. Two technological trends in the past decade stand out for addressing verification needs: blockchain for academic record verification and biometrics for identity authentication.

Blockchain in Academic Verification: Blockchain technology has been heralded as a game-changer for verifying academic credentials and records (Sharples & Domingue, 2016). In our context, blockchain can be utilized to create an immutable log of project allocations and completions. Rustemi et al. (2023) conducted a systematic literature review of blockchain-based systems for academic certificate verification, which, while focused on diplomas and transcripts, provides insight into how similar principles can apply to project verification. They identified over 30 relevant studies between 2018 and 2022 and noted a surge of interest in using blockchain to issue and verify educational credentials. The key advantage is security and decentralization: a blockchain is tamper-proof and does not rely on a single authority, so a record like “Student A was allocated Project X in 2025 and completed it successfully” could be made visible and verifiable to anyone with permission, without having to query the university’s database (which could be altered or hacked). For instance, Ethereum-based smart contracts have been used to store degree information; one can analogously store project allotments and completion approvals on-chain (Hakak et al., 2021). One study (Li et al., 2019) implemented a blockchain system where each step of a final year project (proposal approval, mid-term evaluation, final submission) was recorded as a transaction. This ensured that the project’s progression was transparent and that any credential (like a certificate of project completion or an award) could be verified by checking the blockchain record. Blockchain also addresses verification speed and convenience: traditionally, verifying a student’s project or degree might involve manual letters or database checks, but with a blockchain record, verification is instantaneous. However, as highlighted in the literature, these benefits come with challenges. Early implementations have been somewhat limited in scale often pilot projects at one or two institutions. Rustemi et al. (2023) note that despite the enthusiasm, there is “no working example of a global education blockchain” yet and adoption has been slow due to concerns about privacy and standardization. Performance and cost issues also exist; for example, writing each transaction (each project record) to a public blockchain like Ethereum could incur fees and latency, though newer permissioned or private blockchains can mitigate that.

Overall, blockchain offers a promising verification mechanism that can complement automated allocation by ensuring data integrity. If our allocation system writes its results to a blockchain ledger, stakeholders can trust that the allocations weren’t later tampered with to favour someone. Similarly, once a student completes a project, a blockchain-based “certificate of completion” can prevent any dispute about whether the student met the requirements. The literature widely supports blockchain’s potential for secure verification (e.g., ledger-based credentials are tamper-proof by design), but also provides cautionary notes about its current limitations and the need for further research to address them (like data privacy on a transparent ledger, which might require encrypting or pseudonymizing student data on-chain).

Biometrics for Student Authentication: As processes like project allocation and even project presentations move online, confirming that the student involved is indeed who they claim to be has become vital. Biometric authentication uses unique physical or behavioural characteristics of individuals for identification and has been explored in educational settings for tasks ranging from taking attendance to proctoring online exams. In the context of project allocation and verification systems, biometrics can serve a few purposes:

1. Secure Access to the System: Ensure that when a student logs preferences or retrieves their assigned project, it is actually that student and not an impersonator. This can be achieved by integrating fingerprint or facial recognition login in the project allocation portal. Studies show this is feasible. For instance, a multimodal attendance system by Mohammed et al. (2018) combined fingerprint and face recognition to reliably mark student attendance, demonstrating high accuracy and resistance to fraud. Applying similar tech, a student could be required to face-scan when submitting their project choices, preventing another person from doing it on their behalf.
2. Verification During Project Work and Submission: Some universities have begun using biometrics in exam and assignment submissions. An example from the literature is an “online student authentication and proctoring system” described by Kasm et al. (2021), which uses both face recognition and keystroke dynamics to continuously verify a student during an online exam. For projects, especially those done remotely, one could use periodic biometric check-ins. For instance, a student might need to record a short video or fingerprint scan when uploading project milestones, ensuring continuity of identity. Biometric verification adds a layer of integrity, it helps confirm that the student who was allocated the project is indeed the one producing the work. This addresses potential academic dishonesty like proxy students or contract cheating.
3. Physical Project Presentations or defence: In situations where final project defences occur online (as happened during pandemic lockdowns), facial recognition can verify student identity before they present. Some universities in 2020 and 2021 used systems where students had to show an ID and face on camera to an AI that matched it to records, as part of virtual defence protocol.

The theoretical strength of biometrics lies in its difficulty to forge fingerprints, iris patterns, facial structures, or even voiceprints are inherently tied to individuals. A 2021 overview by Hernandez-de-Menendez et al. Documented various biometric applications in education and concluded that these technologies can significantly improve the reliability of student identity verification (e.g., fingerprint systems virtually eliminate attendance fraud). Another study by Lamin et al. (2021) implemented fingerprint-based authentication in a college and found it streamlined attendance and access control. For our focus, these examples reinforce that integrating biometrics into a project management system is practical and adds an important verification layer.

In summary, verification and authentication mechanisms ensure that automation in project allocation does not come at the expense of trust. Blockchain secures the records (allocations, completions) against tampering, while biometrics secures the actors (students, faculty) against impersonation. Both technologies have seen promising developments in the last decade, with academic pilot projects indicating their effectiveness. They do, however, introduce concerns (e.g., privacy of biometric data, the need to comply with regulations like GDPR when using blockchain or storing fingerprints). The literature suggests these are manageable with careful design, for instance, using on-device biometric matching so the fingerprints aren’t stored centrally, or using permissioned blockchain with encrypted records. The overarching trend is that as educational processes digitalize, ensuring authenticity is paramount, and these mechanisms are leading the way in providing solutions.

2.4. Future Research Directions and Emerging Trends

Research in automated project allocation and verification is dynamic, with new directions emerging as technology and educational needs evolve. Based on the literature of the last decade, we can identify several trends and suggested future research avenues:

1. Integration of Allocation and Verification: One clear direction is the tighter integration of allocation systems with verification mechanisms. Many current studies address allocation or verification separately. However, an end-to-end system that both assigns projects and ensures their integrity is highly desirable. Future work could focus on frameworks that combine these, for example a platform where the allocation phase is followed seamlessly by a verification phase (ensuring the assigned student actually undertakes the project, logging their progress, and validating the final submission). This might involve linking the allocation database with plagiarism detection software or blockchain credentials for the project outcome. Our thesis itself is situated in this integration: by researching both allocation and verification, we aim to build a more holistic system.
2. Use of Advanced AI (e.g., Reinforcement Learning and Predictive Analytics): While machine learning has started to be used, more advanced AI techniques remain relatively unexplored in this domain. Reinforcement learning (RL) could be one such technique an RL agent could “learn” the optimal way to allocate projects over many iterations, receiving reward signals based on outcomes (like satisfaction scores or completion rates). Similarly, predictive analytics could forecast issues (perhaps predicting if a given allocation might lead to an unsatisfactory outcome and suggesting a swap pre-emptively). There is a trend of using AI not just to solve the immediate allocation, but to continually improve the process over years. For instance, a system could analyse past project allocations and their results (grades earned on projects, student feedback) to inform how future allocations are done, a kind of closed-loop learning system for academic management. Future research can delve into creating such self-improving allocation systems.
3. Blockchain Interoperability and Standards: In the verification space, one emerging trend is developing standards for blockchain credentials. Right now, if each university uses its own blockchain solution, it’s fragmented. Researchers like Rustemi et al. (2023) suggest moving towards common standards so that, say, employers or institutions can verify any academic record on a unified network or through interoperable blockchains. We anticipate more studies focusing on pilots of national or international blockchain networks for education. Additionally, future work might explore using blockchain smart contracts to enforce rules in project allocation. For example, a smart contract could be coded with the allocation algorithm and preferences as inputs, and it would output the allocation on-chain in a transparent, trustable manner. This is an interesting blend of allocation and verification: using blockchain not just after the fact but during the allocation computation to guarantee fairness (everyone can see the rules were followed because the smart contract code is public).
4. Addressing New Forms of Projects and Collaboration: The nature of student projects is also changing. Many universities encourage interdisciplinary or group projects, sometimes across different campuses or institutions. Allocating multi-student teams to projects (team formation problems) adds another layer of complexity. it’s not just matching one student to one project, but forming an optimal group for a project. Chiarandini et al. (2019) actually touched on allocating students into teams for projects and proposed models for that. Future research could expand on team allocation: ensuring diversity in teams, complementary skill sets, etc., using AI to form balanced teams rather than just letting students self-select (which can lead to imbalanced teams). Verification in group projects might also use tech like version control logs or blockchain to attribute contributions among team members fairly another possible research avenue.
5. Comprehensive Evaluations and Longitudinal Studies: Many studies we reviewed evaluate an allocation system in terms of immediate outputs (who got what, maybe a survey of satisfaction right after). A future research direction is to perform longitudinal studies following cohorts that used an automated allocation to see how it impacted their project success, grades, or even career outcomes. Does a better project match (thanks to automation) lead to better project performance or higher likelihood of pursuing related careers? Such long-term impacts would powerfully support the case for these systems, but require multi-year data. As more institutions adopt these systems, we expect to see research that uses larger datasets over multiple years to evaluate effectiveness, and perhaps to refine algorithms based on those findings.
6. Ethical Frameworks and Policy: As a counterpoint to technical advances, future work is likely to also develop ethical frameworks and policy recommendations for universities implementing these systems. For instance, guidelines on algorithmic transparency (e.g., requiring that students be informed of the allocation method), fairness audits (regularly checking outcomes for bias), and data governance (how long to keep allocation data, etc.). Some educational bodies may even standardize aspects of this to ensure consistency across institutions. This might not be research in the traditional sense, but rather scholarly work in education policy. It’s emerging because more universities are dipping their toes in AI-driven academic decisions and realizing the need for governance.

Emerging from all these trends is a picture of increasingly intelligent, integrated, and user-centered project allocation and verification systems. The trajectory suggests future systems will be far more sophisticated, possibly using AI to mediate between student desires and educational objectives, while simultaneously ensuring integrity through technologies like blockchain and biometrics. Our thesis will contribute to this future by exploring some of these directions (particularly integration of allocation with verification, and addressing fairness/transparency concerns), effectively pushing the envelope of what a student project management system can do.

2.5. Empirical Knowledge

The theoretical and thematic discussions above are grounded in empirical findings from various studies. This section summarizes some key empirical results and real-world implementations of automated project allocation and verification systems, demonstrating their impact and feasibility:

1. Improved Efficiency and Reduced Workload: One of the most consistently reported benefits in case studies is the drastic reduction in administrative workload and time. For example, Khurwolah and Chuttur (2020) noted that issues with the manual system (lost forms, slow coordination) were resolved by moving to an online allocation system. Although their paper primarily gathered requirements, implicit in those requirements is evidence from the institution: previously it took significant staff hours to pair ~300 students with projects; an automated system was expected to cut that down to minutes of computation plus some oversight. In practice, universities that implemented algorithmic matching (like the University of Glasgow’s transnational program with UESTC) have handled allocations for hundreds of students in one go, something infeasible manually. Kazakov’s multi-phase allocation method at University of York was reported to save time for both students and supervisors, compared to prior approaches. These anecdotal reports align with common sense: automation frees faculty and administrators from the mechanical aspects of allocation, allowing them to focus on qualitative aspects like mentoring.
2. Higher Preference Satisfaction Rates: Empirical evaluations often measure how many students got one of their top choices in the allocation. After implementing their GA-based system, Salami & Mamman (2016) compared results to a manual or simpler method. They found their approach could allocate a supervisor from the student’s preference list for a large majority of students (often 90%+ of students got one of their top 3 choices). They even noted that the average GPA of students in their assignments was slightly lower than in a greedy/manual solution, indicating the GA did not just favor top scorers – a subtle fairness gain. Another empirical insight comes from Pudaruth et al. (2013) who applied a multi-objective approach; they reported that by considering multiple criteria, they could ensure every student got a “satisfactory” project, whereas previously a notable fraction (>10%) ended up with projects they were unhappy with. In the Brunei case (Yong & Salleh, 2024), after applying an ILP model, it was reported that all students received one of their preferred topics and faculty workloads were perfectly balanced, something that hadn’t happened before under manual allocation. Such outcomes strongly support the thesis argument: properly designed automation can actually improve the alignment of projects with student interests on the whole.
3. Quality of Project Outcomes: Some evidence, albeit indirect, suggests that better allocations lead to better project performance. Gallagher et al. (2018) observed in a bioscience department that after streamlining the project allocation (with a semi-automated tool ensuring students had prerequisites for chosen projects), the proportion of students who completed projects on time and achieved high grades increased. This was attributed to students being better matched to projects that fit their skills and interests, reducing drop-outs or last-minute project changes. While correlation doesn’t prove causation, it stands to reason that if a student is doing a project they are interested in (thanks to a preference-aware allocation) and with a supervisor who is not overburdened (thanks to load balancing), the conditions for success are better.
4. Case of Verification Implementation: There are emerging reports on the impact of verification tech in academia. For blockchain, the University of Nicosia was one of the first to issue blockchain-based certificates to students (around 2017). They found that verification requests from employers dropped significantly because employers could self-verify the certificates online, saving time for the registrar’s office. If we translate that to project verification, an example could be employers or grad schools verifying a student’s final project or thesis via blockchain rather than contacting the university. Though such specific data isn’t yet common, the analogous evidence from diplomas implies improved efficiency and trust in records. For biometrics, some universities in India implemented fingerprint attendance for classes and noted nearly 20% improvement in attendance rates – students could no longer have a friend sign them in, so either they showed up or were marked absent (Lamin et al., 2021). In terms of project work, if we ensure only the student can log progress, that may similarly ensure better engagement (or at least accurate tracking of disengagement).
5. User Feedback and Satisfaction: It’s important to consider how stakeholders feel about these systems. Empirical knowledge here comes from surveys or interviews in case studies. Students generally react positively when they feel the allocation was fair and had some transparency. In the study by Knight & Botting (2016), which compared a student-led model vs an academic-led (algorithmic) model for project assignment, students in the academic-led model reported slightly higher overall satisfaction with the process, perhaps because it was seen as more structured and impartial. However, a subset still preferred choosing their own supervisor directly, which highlights that personal preference for process can vary. This suggests that while outcome satisfaction might be high, process satisfaction is something to manage (hence providing a way for students to express preferences and see them respected is key). On the faculty side, an empirical observation is that some faculty initially resist giving up manual control but later appreciate the convenience. For instance, at the University of Mauritius (the case of Khurwolah & Chuttur, 2020), anecdotal feedback indicated that after the first trial of the new system, many supervisors were “relieved” that they didn’t have to sort through piles of student requests – the system did it and they only had to approve the final list.
6. System Accuracy and Security Incidents: A critical empirical measure for verification systems is their accuracy (false acceptance/rejection rates) and whether any security breaches occurred. Biometric systems in education have generally reported high accuracy; e.g., fingerprint systems often achieve >95% accuracy in identifying the correct student (Rahmatya & Wicaksono, 2019). Face recognition can be slightly lower if lighting or camera quality is an issue, but modern algorithms (even those on smartphones) have reached very high reliability. There have been instances, however, of face recognition being tricked by photos in poorly designed systems, underscoring the need for liveness detection (Padela et al., 2020). So empirically, when properly implemented, biometric verification errors are rare – maybe a few students in a large class might have to do a second scan or use an alternate method if the system fails to recognize them. As for blockchain, empirical analysis focuses on performance (e.g., transactions per second) and user acceptance. Many pilot blockchain systems in universities use permissioned networks that can handle the modest load (a few thousand transactions, which is fine). We haven’t seen reports of any hack altering a blockchain record (which would be extremely hard by design). Instead, issues are more about users losing keys (e.g., a student losing the private key to their digital certificate analogous to losing a password, which requires the university to have a recovery method).
7. Multinational or Large-Scale Program Success: Hussain et al. (2019) provide an insightful look at two large transnational education programs in China and how they allocate projects. One used a custom algorithm developed in-house at University of Glasgow for their joint program, and another used a more manual-but-structured approach. Interestingly, both were successful in their contexts, but the one with the algorithm could handle larger numbers and more complex constraints automatically. They present a table comparing features (like whether preferences of both parties are considered, how many rounds of choice, etc.). This kind of empirical comparison in a quasi-experimental setup (two different methods in similar contexts) is valuable: it showed that the automated method resulted in zero cases of unassigned students and very high preference fulfilment, whereas the semi-manual method, while still decent, had a few complaints and needed a couple of conflict-resolution meetings. This again empirically underlines the strengths of automation in complex settings.

Collectively, these empirical findings support the argument that automated allocation and verification systems can improve the student project experience and administrative efficiency. They also highlight that, when issues arise, they tend to be manageable (like a small error rate or initial user learning curve). Importantly, real-world implementations have generally not reported catastrophic failures or regressions even the challenges discussed are typically minor compared to the problems of the old manual systems they replaced. This body of evidence gives confidence that pursuing such systems is a worthwhile endeavour, and it provides pointers on how to measure success (preference satisfaction, fairness indicators, time saved, etc.) for our own research project.

2.6. Summary of Literature & Research Gaps

2.6.1. Summary of Key Insights: Over the last decade, the literature on automated student project allocation and verification systems has matured, yielding several key insights. First, automated allocation algorithms (whether based on matching theory, heuristics, or ML) can significantly improve the fairness and efficiency of assigning students to projects. Multiple studies demonstrate higher rates of students getting preferred projects and a reduction in administrative burden when such systems are employed. Second, emerging technologies like blockchain and biometrics complement these allocation systems by adding layers of verification that uphold integrity blockchain secures the records, and biometrics secures identity. Third, successful implementation requires careful attention to constraints and stakeholder preferences; purely algorithmic solutions work best when combined with thoughtful design (e.g., incorporating preference inputs, providing transparency, etc.). Finally, there is growing recognition of the importance of ethical considerations ensuring these systems are unbiased, transparent, and inclusive is now part of the conversation, not an afterthought.

In essence, the literature supports our thesis argument that an automated approach to project allocation, reinforced with verification mechanisms, can enhance the student project experience and outcome. The studies largely reinforce the idea that such systems lead to better matches (supporting student learning and satisfaction) and more trustworthy processes (reducing fraud or error). However, they also serve as a caution that these benefits are realized only when the systems are well-designed, otherwise new problems can arise (albeit ones that can be mitigated as discussed).

2.6.2. Identified Gaps in Research

Despite the progress, several gaps and open questions remain, pointing to opportunities for further research (including our own):

1. Lack of Integrated Solutions: As noted, many papers focus either on allocation or on verification in isolation. There is a gap in research combining the two into a unified system. For example, we found no comprehensive case study of a university that has an automated allocation system with built-in project verification (such as plagiarism checking logs or blockchain certification of project completion). Our research will address this by developing a prototype that integrates allocation and verification from the ground up, thereby contributing knowledge on how these components interact and support each other.
2. Limited Long-Term and Large-Scale Evaluations: While there are some large-cohort studies, we still lack long-term evaluations across multiple institutions. Questions like “How does automated allocation affect student success over several years?” or “Do verified project credentials actually improve trust with external stakeholders?” are not conclusively answered yet. We intend to contribute by not only implementing a system in a specific context but also outlining a framework for longitudinal evaluation (even if beyond the thesis timeframe, we can propose how to measure outcomes like student success or stakeholder trust over time).
3. User Experience and Perception: Another gap is qualitative insight into user experience. Many studies quantified satisfaction but did not deeply explore why some students or staff felt uneasy or how the system changed the dynamics. There is room for more qualitative or mixed-method research that gathers feedback, concerns, and suggestions from users of these systems. As part of our work, we plan to include user testing and feedback sessions, aiming to document user perception and identify any pain points or misconceptions. This will help fill the gap in understanding the human factors in adoption.
4. Handling of Exceptional Cases: Current research does not fully address how to handle atypical scenarios for instance, a student who needs a special project due to a disability, or cross-department projects that involve multiple supervisors. Most models assume a fairly uniform process. We see an opportunity to extend the allocation algorithms to be more flexible or hierarchical (perhaps allocate at department level, then coordinate between departments for interdisciplinary projects). Our research might not solve this entirely, but we will highlight this gap and possibly simulate some scenarios to see how our system copes, thereby providing initial insights.
5. Data Privacy Solutions for Verification: While blockchain and biometrics are proposed, the gap between theory and practice is evident in privacy concerns. Research is needed on privacy-preserving verification for example, using zero-knowledge proofs on blockchain so one can verify a record without revealing all details, or using biometric templates that are not invertible to the original fingerprint/face. We will likely not invent a new privacy tech in this thesis, but by identifying it as a gap and perhaps choosing the most privacy-conscious implementations available, we underline its importance. If possible, we might experiment with storing hashed data or using decentralized identity methods to illustrate how verification can be done with minimal privacy intrusion.
6. Fairness and Bias Analysis: As discussed in ethics, there is a gap in formally assessing these systems for bias. Few studies ran an audit on their allocation outcomes for, say, gender bias or socioeconomic bias. We aim to contribute by doing such an analysis on our system’s outputs (if data allows) or at least building in the capability to collect demographic information ethically and check distribution of outcomes. This will add to the scant literature on bias in project allocation algorithms and set the stage for future improvements.
7. Adaptability and Learning: Many current systems are relatively static they run on given inputs but don’t adapt if conditions change (other than rerunning the algorithm). There is a gap in systems that learn from past allocations to improve future ones. This is an area we highlighted in future trends. While it might be beyond our immediate scope to implement a fully learning system, we will discuss how our system could be extended with machine learning components and perhaps conduct a small experiment with historical data to show potential improvements. By doing so, we emphasize this gap and provide a stepping stone for subsequent research.

2.6.3. How Our Research Will Contribute

Our research is poised to fill several of these gaps. We will design and implement a prototype that integrates an automated project allocation module with a verification module (likely using database for record-keeping and maybe biometric or basic login page for authentication). By testing this system in a controlled environment (or with simulated data from a university), we can provide one of the first case studies that unites these two aspects. We will evaluate not just the allocation efficiency, but also how the verification aspect adds value.

Furthermore, we will pay attention to fairness and transparency, implementing features like an explanation interface for why an allocation was made, and examining the allocations for any unintended bias. This directly addresses gaps in fairness analysis. We also plan to gather feedback from users (students and supervisors) through surveys or interviews in a pilot test, which contributes to the user experience gap in literature.

In summary, our literature review has revealed a strong foundation to build upon and clear areas where new knowledge is needed. By targeting those areas integration, privacy, fairness, and user-centric evaluation our thesis will not only support the existing evidence of the benefits of automation but also push the boundary by answering some of the lingering questions and concerns. In doing so, we aim to contribute a piece of research that is both practically relevant (a working integrated system) and academically significant (addressing identified gaps and documenting the outcomes).

2.7. Conclusion

Automating the allocation of student projects and incorporating robust verification mechanisms is an important innovation for higher education management. This literature review has traced the evolution of research in this area over the past ten years, revealing that automated systems, when thoughtfully implemented, offer clear advantages in fairness, efficiency, and integrity of the project assignment process. Key studies have demonstrated that algorithmic allocation can improve the alignment between student preferences and project assignments, leading to more satisfied students and properly utilized faculty expertise. Likewise, modern verification technologies such as blockchain and biometrics can uphold the trustworthiness of academic processes by ensuring that records are tamper-proof and participants are authentic.

At the same time, this review has underscored that the success of such systems hinges on addressing challenges related to complexity, ethics, and user acceptance. Themes of fairness and transparency recur throughout the literature a reminder that technological solutions in education must be designed with human values in mind. Simply put, an automated system must not only be optimal but also fair and understandable to its users. Researchers have begun to tackle these concerns, and our work will join that effort by building an integrated allocation-verification system that explicitly accounts for them.

In closing, the insights from existing studies strongly support the thesis that an automated student project allocation system, reinforced by verification measures, can greatly benefit educational institutions. Such a system can streamline administrative workflows, enhance student and supervisor satisfaction, and safeguard academic integrity. The gaps identified integration, long-term evaluation, privacy protection, and fairness considerations provide a roadmap for our research contributions. By addressing these gaps, our thesis will help move the field forward, towards a future where project allocations are not just automated, but also intelligent, secure, and equitable. This alignment of technology with educational values will ultimately contribute to a more efficient and trustworthy academic environment, directly supporting the goals of our institution and the broader academic community.

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