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COMPARATIVE ANALYSIS OF CHALLENGES IN MANUAL AND AUTOMATED CONSTRUCTION PROGRESS MONITORING IN SRI LANKA

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ABSTRACT

Construction Progress Monitoring (CPM) plays a pivotal role in ensuring the timely and cost-effective completion of construction projects. Previous research has classified CPM techniques into manual and automated methods. While traditional manual CPM has been prevalent in the Sri Lankan construction industry, it suffers from several limitations that can impede project success. Despite the significance of CPM, both manual and automated techniques face challenges in implementation. Therefore, the research aims to explore the challenges associated with CPM in the Sri Lankan construction industry. A comprehensive literature review was conducted to establish a theoretical framework. A quantitative research approach was employed, utilising a questionnaire survey with a heterogeneous purposive sampling method, involving 68 respondents. Data analysis was performed using IBM SPSS software. The study revealed different challenges in manual CPM and automated CPM specifically within the Sri Lankan context. One of the key takeaways of this study is that the challenges in manual CPM outweigh those in automated techniques. However, statistical analysis indicated that both manual and automated CPM face significant challenges, as evidenced by a negative skewness in survey data. Automated CPM heavily relies on computer vision technologies, with issues primarily arising from reality-capturing technologies. This study significantly contributes to the existing body of knowledge by identifying and categorising challenges in both manual and automated CPM within the Sri Lankan construction industry. The findings provide a platform for future research endeavours to devise strategies and solutions to address these challenges, ultimately enhancing the efficiency and effectiveness of construction progress monitoring in the industry.

Keywords: *Automated Progress Monitoring; Challenges; Construction Progress Monitoring (CPM); Manual Progress Monitoring; Sri Lanka.*

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1. INTRODUCTION

The construction industry plays a vital role in contributing to the economy of the nation (Parameswaran & Ranadewa, 2024). However, the construction industry is plagued by project delivery delays, and cost overruns (Amri & Marey-Pérez, 2020; Parameswaran et al., 2024). Han et al. (2018) stated that, although project managers allocate a considerable priority to project schedule and budget adherence, due to the failure to effectively capture construction progress more than 66% of projects are cost overrunning, and 53% of projects are getting delayed. In addition, Alizadehsalehi and Yitmen (2019) stated that time, cost, and quality are the key indicators in the progress of a construction project which can impact the project during the construction period. Most researchers have identified that CPM can influence a project's time, cost, and quality aspects (Ingle & Mahesh, 2022). Khairadeen Ali et al. (2021) stated that CPM can be used to overcome scheduled delays and budget overruns. Ekanayake et al. (2021) mentioned that CPM is critical for determining progress discrepancies between as-planned and as-built status and for taking corrective actions on time. In compliance with these statements, the CPM can be considered an essential aspect of project control that supports making timely decisions to ensure successful project delivery (Rehman et al., 2022). Therefore, it is vital to monitor the progress on construction sites during the construction period as CPM benefits the project by cost savings, time shortening, and quality improvement (Fobiri et al., 2022). To achieve the benefits, different CPM techniques have been followed by the industry people for instance computer vision techniques (Rehman et al., 2022), visual and virtual techniques (Lin & Golparvar-Fard, 2020), reality capturing techniques (Jacob-Loyola et al., 2021). Therefore, both automated and manual CPM techniques can be identified in the construction industry.

Automated CPM is defined as the process of using technology and data analysis to monitor construction projects in real time, with less labour involvement (Kopsida et al., 2015; Perera et al., 2023). Manual CPM is considered where the whole process of monitoring will be done with human involvement and primitive technology will be adopted and based on labour (Qureshi et al., 2022). In addition to that, manual techniques are time-consuming (Silva et al., 2015) and less accurate (Wang et al., 2015). Despite the importance of CPM, there are several challenges in manual progress monitoring methods (Dasović et al., 2020; Reja et al., 2022) and automated CPM techniques (Christou et al., 2021; Qureshi et al., 2022; Rodríguez et al., 2022). Thus, there is a need to investigate the challenges of manual and automated CPM. Therefore, the research aims to investigate the challenges in CPM in the Sri Lankan construction industry. The objectives of the research are to identify the challenges of manual and automated CPM. This paper commences with a literature review on challenges in manual CPM and challenges in automated CPM techniques. Thereafter, the research methodology adopted is presented. The next section presents an analysis of empirical data in terms of challenges in manual CPM and automated CPM techniques, and the overall mean comparison to challenges between manual and automated CPM techniques.

2. LITERATURE REVIEW

2.1 CHALLENGES IN MANUAL CPM

Despite the importance of CPM, manual progress monitoring methods can be difficult. Table 1 emphasises the major challenges that are faced by the project managers by incorporating manual CPM methods. The following categorisations have been done with the level of human involvement for each technique.

Table 1: Challenges in manual CPM

Method		No	Challenges	References
Commercial Software	MS Project and Primavera P6 software.	1	Both software does not allow for drawings and visualization of construction. Therefore, the client is unable to understand.	[1]; [20]
		2	In MS Project software, displaying multiple Baseline bars is difficult.	[2]; [22]
		3	Lack of multi-project control in MS Project.	[19]
		4	Less interoperability between P6 and Microsoft Word.	[2]
		5	Require manual data updating, which is time-consuming and error-prone for both software.	[7], [21]
		6	Both these software programs are quite expensive.	[13],[14],[15]
		7	Primavera tools are not arranged properly. Hence, difficult to navigate within the software.	[16]
		8	PDF reports are not supported by Primavera P6.	[17]
		9	Both software does not support real-time (Automated) updates without integration.	[18]
	4D Modelling Software.	10	Determining who will oversee entering BIM data into the model and ensuring its accuracy and consistency is a risk.	[23]
		11	Require manual data updating, which is time-consuming and error-prone.	[24],[25],[26]
		12	Limited adoption of progress monitoring tools.	[27]
Earned Value Manageme nt.		13	Hugely influenced by material prices and labour rates.	[11]
		14	Lump-sum price breakdown is necessary to calculate the BCWP value.	[5]
		15	Measures only 'amount of work performed', but time deviations are not considered.	[6]
Physical Measurement Techniques.		16	Labour incentives, involve paperwork and are time-consuming.	[7]
		17	Manual, lengthy drafting and updating process.	[15]
		18	Manual data collection makes the process inaccurate.	[9],[10],[11]
		19	Reliance on the supervisor's determination and integration of cost with time, and scope of work into progress measurement is difficult.	[9],[12],[27]

[1] - (Reja et al., 2022) , [2] - (Phophalia & Basu, 2018), [3] - (Puri & Turkan, 2020),[4] - (Christensen, 1998), [5] - (Bhosekar & Vyas, 2012), [6] - (Ballesteros-Pérez & Elamrousy, 2018), [7] - (Zaher et al., 2018), [8] - (Xu et al., 2021), [9]- (Danku et al., 2020),[10]- (Ibrahim et al., 2009), [11] - (Ergen et al., 2007), [12]- (Ibrahim et al., 2009), [13] - (Alaidaros et al., 2019), [14] - (Azhaman et al., 2021), [15]- (Nyandongo & Lubisi, 2019), [16] -(Pankaj et al., 2020), [17] –(Khairadeen Ali et al. 2021), [18] – (Perera et al., 2023) , [19] -(Wali & Othman, 2019), [20]- (Noaman & Al-Taie, 2020), [21] - (Dasović et al., 2020), [22] - (Deshmukh et al., 2019), [23] - (Ahmadi & Arashpour, 2020) , [24] -(Kropp et al., 2012), [25] -(Kim & Lee, 2019), [26] - (Silvestre & Ţîrcă, 2019), [27] - (Álvares & Costa, 2019)

According to Table 1, most of the researchers have emphasised that the MS Project and Primavera P6 software are quite expensive. In addition to that, researchers have identified that manual data updating is demanded by this software which can be prone to errors. Importantly, several researchers express that progress understanding is quite hard when visualisation is not supported by this software. Besides, most researchers indicated that 4D modelling software also demands manual data updating when automated technologies are not integrated for data capturing. A major challenge in Earned Value Management (EVM) is that it is only used for financial progress measurement purposes while a separate technique should be followed for physical progress. When considering the physical measurement techniques, their results are subjective because they depend on the supervisor's decisions. Besides Omar et al. (2018) stated that these manual CPM processes are extremely slow, as updating the construction activities requires approximately 20-30% of the feeders' daily efforts. Therefore these, manual progress monitoring methods are currently unable to keep up with the industry's rapid development (Sidani et al., 2021).

Omar et al. (2018) further stated that manual CPM is outdated due to the various challenges faced by the progress inspectors. Pan and Zhang (2021) highlighted that manual progress-tracking methods have limitations in studying project progress precisely. Therefore, Puri and Turkan (2020) highlighted that the challenges in manual progress-measuring approaches emphasise the importance of implementing modern technologies for CPM. As a recent trend, automated CPM is trying to find answers to these issues (Shamsollahi et al., 2022)

2.2 CHALLENGES IN AUTOMATED CPM TECHNIQUES

Researchers have reviewed that computer vision is not still a regression as it is improving (Wang et al., 2021), yet it has faced challenges that have prevented it from being widely adopted in the construction industry. Despite the success of computer vision technology, automated CPM is still quite a challenge due to many challenges in the use of various data-collecting methods (Pučko et al., 2018). These challenges are listed in Table 2.

Table 2: Challenges in existing CPM

Method	Technology	No	Description	Reference
Point cloud and 4D BIM-based technologies.	3D laser scanning	1	High expensive equipment, mixed pixel restoration, need for sensor calibrations regularly, greater warm-up time.	[1];[2];[3];[4];[5]
		2	Operation requires high technical knowledge.	[6]
		3	The accuracy of the data acquisition using laser scanning might be affected due to occlusions and shadows in the site.	[7]; [8]
	Light detection and ranging scanning (LiDAR).	4	LiDAR data processing refers to the use of algorithms due to unorganized point clouds occurring by dynamic scanning.	[9]
		5	Require expert operators when the sensor platform flies through narrow pathways.	[10]
		6	Large empty voxels may cause the loss of information, which will reduce the accuracy of data processing.	[11]
	Photogrammetry	7	Differences in lighting conditions may affect the resolution.	[12];[13]
		8	Object edge detection may be affected. Moreover, shadows, occlusions, and noisy images will affect the accuracy of progress estimation.	[14];[15]
		9	Noisier point clouds than LiDAR.	[16]
		10	The accuracy level in point cloud models depends on the number of photographs.	[17];[18]
		11	Photogrammetry scanning is a lengthy process that needs a lot of software knowledge.	[19]
		12	Large-scale construction projects may become exceedingly labour-intensive and error-prone.	[20]
	Videogrammetry	13	Highly get affected by occlusions.	[21]

Method	Technology	No	Description	Reference
	Time Lapse Camera	14	Adjacent buildings or elements (temporary or permanent) affect the visual quality of photographs. Varying lighting, shadows, weather, and site conditions complicate image analysis. Display only what is in the range and view field.	[22]
	CCTV Camera	15	Fixed cameras increase the number of cameras required. Less field of view can be caused by data clashes.	[23]
Sensor-based technologies.	Quick response or QR codes.	16	Might be damaged by environmental conditions.	[24]
		17	Object tracking is difficult for some materials, which are not easily accessible.	[25]
	Radio Frequency Identification or RFID tags.	18	RFID tags are usually developed with a fixed single sensor or, multiple built-in sensors which results in limited flexibility.	[26]
		19	Blind spots may occur when the RFID tag is not in the coverage area of the receiver.	[27]
		20	Due to sensors, transceivers, and various devices, energy consumption is high.	[28]
Geospatial technologies.	Geographic Information System (GIS)	21	The main challenge is difficulty in handling in indoor environments. Therefore, most suitable for outdoor progress monitoring.	[29]
		22	Need system developers.	[30]

[1]-(Moon et al., 2019), [2]- (Nguyen et al., 2020) , [3] -(Alshawabkeh et al., 2021), [4]- (Dreier et al., 2021), [5] - (Lassiter et al., 2021), [6] - (Qureshi et al., 2022) , [7] - (Phophalia & Basu, 2018), [8] - (Mwangangi et al., 2022) , [9] - (Paiva et al., 2023) , [10] - (Weinmann et al., 2021), [11] -(Gharineiat et al., 2022), [12] - (Ventura et al., 2021), [13] -(Peng et al., 2021), [14] - (Reja et al., 2022), [15] – (Barbero-García et al., 2021) [16]- (Latella et al., 2022), [17] - (Rodríguez et al., 2022), [18]- (Štroner et al., 2021), [19] - (Omar et al., 2018), [20] - (Rahimian et al., 2020), [21]- (Alaloul et al., 2021), [22]-(Golparvar-Fard et al., 2009), [23] -(Reja et al., 2022), [24] -(Wang et al., 2021), [25] -(Zhai et al., 2019), [26] -(Landaluce et al., 2020), [27]-(Shirehjini & Shirmohammadi, 2020), [28]- (Cui et al., 2019), [29] -(Thellakula et al., 2021), [30]- (Christou et al., 2021)

In compliance with Table 2, field data-capturing technologies are undermining the existing automated CPM techniques to some extent. Commonly, all these point cloud techniques are used to re-model real-world objects through reality capturing, therefore, all researchers have mentioned that each technique is lighting sensitive. According to Table 2, most researchers have addressed that 3D laser scanning techniques are having many challenges rather to the other techniques. Comparatively, challenges in Photogrammetry techniques were also highly reviewed by the researchers that emphasise the difficulties in that technology. However, this literature review identified that still automated reality-capturing techniques can be used for CPM due to fewer references to the challenges in other technologies except for several techniques. Nevertheless, researchers further emphasised that reality-capturing technologies in the CPM are still connected with BIM (Alaloul et al., 2021; Arif & Khan, 2021; Kavaliauskas et al., 2022). Therefore, it is important to review the research findings regarding the challenges in BIM. Szeliski (2022) stated that engineers face difficulties while managing complex 3D models. Besides, (Li et al., 2022) mentioned that BIM modelling demands high-performance servers for rendering, and it takes a long time to complete the rendering procedure. Johansson and Roupé (2019) expressed that BIM applications are constantly improving, but there are issues with the user interface, and extracting information and taking correct measurements directly from the model is difficult. For this reason, information transfer from the design office to the construction site is delayed. Because of these difficulties, most of the BIM-integrated CPM techniques have become a challenge. In this case, researchers have identified the optimum use of XR technologies and BIM-integrated computer vision-based CPM techniques. Together these technologies successfully visualise the progress deviations by superimposing BIM models to the construction images over a 3D model (Ekanayake et al., 2021).

Exploring the critical significance of CPM, both manual and automated approaches encounter various challenges. Hence, there is a need to investigate the challenges of both manual and automated CPM. Therefore, the research aims to investigate the challenges in CPM in Sri Lankan construction.

3. RESEARCH METHODOLOGY

The study started with a comprehensive literature review. Questionnaires are frequently utilised in survey methodologies since they offer an approach to collecting responses from a large sample, ensuring uniformity in questioning, and enabling effective quantitative analysis (Saunders et al., 2009). Therefore, a questionnaire survey was used to collect the data. Accordingly, challenges to existing CPM techniques were identified through a questionnaire survey. The selected population for the questionnaire survey was the professionals who have addressed the CPM in local and international level project delivery. The heterogeneous purposive sampling technique was used for quantitative approaches to select a representative sample from the population as it assisted in selecting a sample that is relevant to a range of experiences, perspectives, and characteristics (Mweshi & Sakyi, 2020). In this study, a heterogenous sampling technique was adopted since it allows to choice of professionals know about automated and manual CPM techniques. The sample population was limited to 68 people who are engaged in CPM techniques in the industry representing different educational levels, professions and experiences within the construction industry. Furthermore, a questionnaire survey was conducted through the Google Forms platform, requesting ratings on the challenges to CPM that were identified. Majorly, the questionnaire survey requested to rate the challenges related to both automated and manual CPM techniques for a given scale. The scale for the ratings was a five-point “Likert scale” that was requested to rate the level of significance of each challenge in both CPM techniques, where 1 meant "Strongly disagree" and 5 meant "Strongly Agree (Parameswaran & Ranadewa, 2022).

3.1 PROFILE OF THE SURVEY RESPONDENTS

Figure 1 presents the details of the respondents.

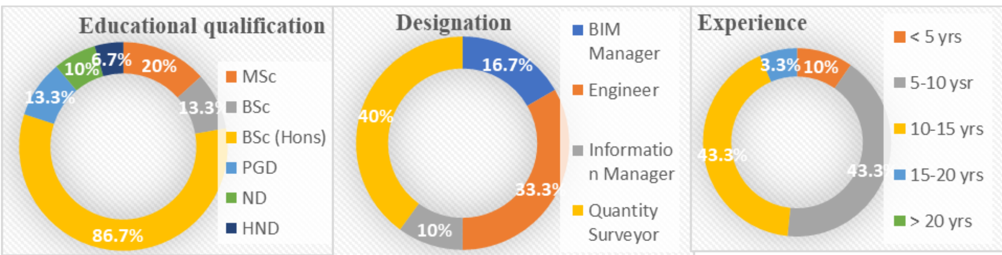

Figure 1: Details of the respondents

The selected sample necessarily had experience in CPM and before sharing the questionnaire a verification was done to ensure the respondent had adequate experience in terms of CPM in both manual and automated techniques. Most of the respondents had experience in the local context except a few respondents who had experience overseas. According to Figure 1, 86.7 % portion of respondents completed BSc (Hons) level educational qualifications. 20% of them completed the MSc. An equal number of BSc degree and Post Graduate Diploma holders represent Figure 1. Higher national diploma holders account for 10% of the chart. The remaining 6.7 % belonged to the National Diploma holders. Figure 1 indicates the designation of each respondent who answered the questionnaire survey. Accordingly, 40% of the respondents were Quantity Surveyors and 33.3% were Engineers.

Importantly, several BIM experts were able to attend the questionnaire. Among them, 16.7% of respondents were BIM Managers while 10% of them were Information Managers. Figure 1 shows the distribution of experience of the respondents among 30 respondents of the questionnaire survey. Similarly, 43.3% of the respondents had experience of 5-10 years and 10-15 years. However, 10% of the sample had less than five years' experience. The remaining 3.3% of the chart is taken by the respondents who had experience for 15-20 years. Challenges in the literature findings related to both manual and automated CPM techniques had to be analysed. Thus, IBM SPSS software was used as a supportive tool that assists the statistical measures of survey data. Accordingly, the central tendency parameters have been considered to determine the suitability to use such parameters to analyse the survey data. The analysis is further discussed by using the statistical parameters on the responses such as Mean, Median, and Mode Standard Deviation and Variance (Ali & Bhaskar, 2016).

4. RESEARCH FINDINGS

4.1 ANALYSIS OF CHALLENGES IN MANUAL CPM

Challenges to manual CPM techniques were identified in the literature review through Table 1, the questionnaire survey was designed to scale the level of significance of each challenge. Thus, Table 3 indicates the statistical parameters on the level of significance.

Table 3: Statistical parameters on challenges of manual CPM

Challenge *No.*	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**
Mean	4.5263	4.5263	4.2368	4.5263	4.1053	4.0526	3.6579	3.7105	4.5789	3.8684	3.4211	3.5000	3.2632	3.9737	4.1316	4.2895	4.7895	4.1842	3.8158
Median	5.0000	5.0000	4.0000	5.0000	4.0000	4.0000	4.0000	4.0000	5.0000	4.0000	3.0000	3.0000	3.0000	4.0000	4.0000	4.0000	4.0000	4.0000	4.0000
Mode	5.00	5.00	4.00	5.00	4.00	4.00	4.00	4.00	5.00	4.00	3.00a	3.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00
Std. Deviation	.79651	.82975	.71411	.86170	.89411	.76925	.93798	.89768	.79293	.52869	1.05604	.95153	1.00497	.54460	.47483	.73182	.89411	.60873	.98242
Variance	.634	.688	.510	.743	.799	.592	.880	.806	.629	.280	1.115	.905	1.010	.297	.225	.536	.799	.371	.965

The results of the questionnaire survey on the challenges to manual CPM techniques have shown the central tendency parameters concerning the Likert scale. The Median and the

Mode of the challenges varied between four and five except for challenges 11, 12, and 13. Therefore, it is decided that most respondents agreed with the identified challenges while others have not decided whether to agree or not. Moreover, in Table 3, it is shown that the distribution of scores was relatively narrow in challenges 1, 2, 8, 9, 10, 14, and 19 because the mean score was slightly lower than the median and mode. When the mean is lower than the median and mode, it implies that there are a few lower scores that are bringing the mean down. Therefore, there is a small number of extremely low ratings because of that it is decided most of the respondents did not rate these challenges under the disagreed level.

Besides, when the Mean value is higher than the Median and Mode, it indicates that there are a smaller number of high ratings on the challenges. The challenges number 11 and 13 show greater Standard deviation on the Mean which cannot be decided on the level of significance using the central tendency parameters. The data set was negatively skewed as emphasised earlier; therefore, the Mean is not suitable for analysing the level of significance of the given data set. However, the Median can be used to analyse the data set as it does not have a greater impact on the skewness. Accordingly, challenges 1, 2, 4, and 9, indicate a higher tendency to the "Strongly agree" statement. However, challenge number 12 remained in the "Undecided yet" category while the rest of the challenges have been rated as "Agreed" level.

4.2 Analysis of Challenges in Automated CPM

Table 4 indicates the statistical parameters for the findings of the questionnaire survey. Accordingly, an analysis of the challenges to the automated CPM that was listed in Table 2 is further discussed herein.

Table 4: Statistical parameters on challenges of automated CPM

Challenge *No.*	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**
Mean	4.5263	4.2222	3.7568	3.7297	3.9189	3.5946	3.5946	3.5405	3.5135	3.5946	3.6486	3.6486	3.5946	3.7297	3.8378	3.7568	3.8889	3.6486	3.6111	3.7297	3.7838	4.0541
Median	5.0000	4.0000	4.0000	4.0000	4.0000	4.0000	4.0000	4.0000	3.0000	4.0000	4.0000	4.0000	4.0000	4.0000	4.0000	4.0000	4.0000	4.0000	4.0000	4.0000	4.0000	4.0000
Mode	5.00	5.00	4.00	4.00	4.00a	3.00	4.00	3.00a	3.00	4.00	3.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00
Std. Deviation	.72548	.76012	.64141	.73214	.92431	.64375	.59905	.55750	.60652	.49774	.67562	.63317	.59905	.50819	.55345	.49472	.74748	.58766	.59894	.60776	.58382	.77981
Variance	.526	.578	.411	.536	.854	.414	.359	.311	.368	.248	.456	.401	.359	.258	.306	.245	.559	.345	.359	.369	.341	.608

In this case, the Mean score has been lowered than the Median and Mode in many challenges such as challenges number 1, 3, 4, 5, 7, 10, 12, 13, 14, 15, 16, 17, 18, 19, 20, and 21. Accordingly, the data set describes the challenges to the automated CPM that have been rated at higher levels of the scale by the respondents. However, the range of the Mean value varied between 3.5135 and 4.5263, while challenge number 9 indicates the lowest Mean and challenge number 1 indicates the highest Mean. Accordingly, respondents may have stated that the most significant challenge is from the 3D laser scanning technique. However, importantly, this data set indicates that overall survey results varied between "Agreed" and "Undecided yet" levels. Because the Mean value of the results varied between 3.5135 and 4.5263 and Standard Deviations remained lower level. The reason could be that most of the automated CPM techniques are not practised in the industry as mentioned in the literature review (Pučko et al., 2018). The Mean has exceeded the Median and Mode in challenge numbers 9 and 22 when it comes to the challenges in automated CPM techniques. According to that result, those are the lower-rated challenges when it comes to the challenges in automated CPM techniques. As mentioned before this data set was negatively skewed, therefore, the Mode has been selected as the comparison parameter. In compliance with that, challenges number 1 and 2 have been highly rated under the "Strongly agreed" while challenge number 9 appears to "Undecided yet" level of significance. Moreover, remain challenges were rated under the "Agreed" level. Compliance with the overall analysis of each CPM technique, the results, showed that there are high negative ratings on the manual CPM techniques. On the other hand, automated CPM techniques that have been discussed in the literature review were significantly unrated by the professionals.

4.3 THE OVERALL MEAN COMPARISON TO CHALLENGES BETWEEN MANUAL AND AUTOMATED CPM TECHNIQUES

The overall Mean in a data set is a statistical measure that represents the average value of all the observations in the data set (Datta & Datta, 2003). It is calculated by summing up all the observations and then dividing by the total number of observations (Barnett, 2004). Comparing the overall Means of two data sets can be useful in many research fields (Demšar, 2006). Therefore, to compare the manual and automated CPM techniques overall Mean of each data set was used. Considering that two data sets following linear graph were developed in Figure 2.

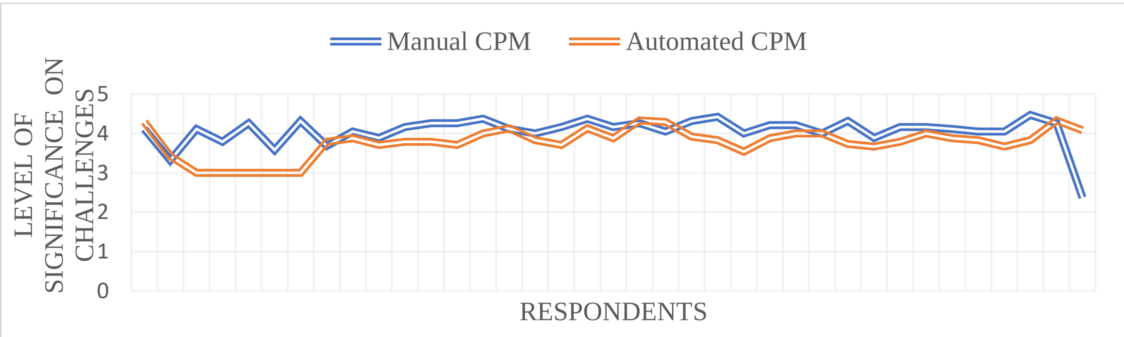

Figure 2: Overall Mean comparison

Figure 2 presents the analysed data on the overall Mean of each manual and automated CPM technique. As shown by Figure 2, manual and automated CPM techniques show a greater deviation from each other because the level of significance on challenges to manual CPM techniques is shown higher significance while the automated CPM techniques are comparatively less. Importantly, the overall Mean has taken a place at an upper level of moderate level of significance which expresses that the literature findings on most of the challenges are truly experienced by the CPM up until now. As appeared in Figure 2, one of the few challenges of both CPM techniques is showing the same overall level of significance as the graphs overlap each other. Finally, the overall analysis of manual and automated CPM techniques has emphasised the importance of an automated CPM technique which can eliminate the challenges in automated CPM techniques that have been analysed in this chapter.

5. DISCUSSION

Azhaman et al. (2021), Danku et al. (2020) and Kim and Lee (2019) pointed out that both software solutions such as MS Project and Primavera P6 software are costly and necessitate manual data updates, leading to time-consuming and error-prone processes and manual data collection introduces inaccuracies, are posing significant challenges in Manual CPM. However, the finding underscored that neither software facilitates drawings and construction visualisation, hampering client comprehension; MS Project struggles with displaying multiple baseline bars, and there's limited interoperability between P6 and Microsoft Word. Furthermore, both platforms lack support for real-time updates without integration, which were highlighted as major challenges. These challenges were strongly acknowledged by respondents in the Sri Lankan construction industry's manual CPM practices, with a high level of agreement observed under the identified 19 challenges. On the other hand, when examining the obstacles within existing automated CPM techniques, Alshawabkeh et al. (2021) and Nguyen et al. (2020) emphasised significant challenges such as the high cost of equipment, issues with mixed pixel restoration, the necessity for frequent sensor calibrations, and longer warm-up times. These challenges were widely acknowledged among respondents, with a notable emphasis on the high expense of equipment, mixed pixel restoration, regular sensor calibrations, and the requirement for extensive technical expertise. Moreover, the challenge relating to noisier point clouds compared to LiDAR was met with uncertainty, indicating a lower level of agreement among respondents. These findings depict that the Sri Lankan construction industry lacks a proper CPM technique which can overcome the identified challenges and obstacles in both manual and automated techniques which are currently available in the construction sector.

6. CONCLUSIONS

The findings of this study provide valuable insights into the challenges faced in both manual and automated CPM techniques. The statistical parameters of this study clearly show the perceived significance of each challenge, allowing for a comprehensive analysis of the responses. In the manual CPM techniques, challenges such as: requiring manual data updating, which is time-consuming and error-prone, limited adoption of progress monitoring tools and is hugely influenced by material prices and labour rates, however, exhibit a certain level of indecision among respondents, suggesting a lack of consensus on these issues. The narrow distribution of scores in challenges includes highly expensive equipment, mixed pixel restoration, the need for sensor calibrations regularly, and greater warm-up time; the operation requires high technical knowledge; object edge detection may be affected. Moreover, shadows, occlusions, and noisy images will affect the accuracy of progress estimation, the accuracy level in point cloud models depends on the number of photographs; adjacent buildings or elements (temporary or permanent) affect the visual quality of photographs. Varying lighting, shadows, weather, and site conditions complicate image analysis. Display only what is in the range and view field; blind spots may occur when the RFID tag is not in the coverage area of the receiver, implying that while most respondents agreed with these challenges, a few lower scores were bringing down the mean.

Moving on to the automated CPM techniques, the mean scores range from 3.5135 to 4.5263, indicating that respondents rated these challenges at higher levels on the Likert scale. The data set suggests an overall agreement or indecision, with mean values falling between "Agreed" and "Undecided yet" levels. Comparing the challenges between manual and automated CPM techniques, the overall mean comparison in Figure 2 reveals a notable deviation. Challenges to manual CPM techniques show higher significance, reflecting the more pressing concerns faced in this traditional approach. Conversely, challenges in automated CPM techniques are comparatively less significant, possibly due to limited industry adoption, as mentioned in the literature review. The overall analysis emphasises the importance of automated CPM techniques in mitigating the challenges faced by manual methods. The Overall Mean Comparison graph in Figure 2 indicates a substantial difference in the level of significance between the two techniques, with automated CPM techniques offering a potential solution to the identified challenges. Finally, the findings of this research highlighted that challenges to manual CPM have a higher level of significance compared to automated CPM techniques. However, the statistical survey results indicated that identified challenges have taken a higher level of significance in both manual and automated CPM as the survey data showed a negative skewness. Automated CPM relies on computer vision technologies. Many issues related to automated CPM techniques have arisen due to the use of reality-capturing technologies.

This paper provides a comprehensive analysis of the challenges encountered in both manual and automated construction progress monitoring in Sri Lanka. By systematically comparing these challenges, the paper offers valuable insights to industry practitioners, enabling them to understand the limitations and obstacles associated with different monitoring approaches. Through the detailed examination of empirical data, this paper offers practical guidance to stakeholders involved in construction progress monitoring in Sri Lanka. By understanding the specific challenges inherent in manual and automated monitoring methods, practitioners can make informed decisions regarding the selection and implementation of monitoring techniques, ultimately improving project efficiency and performance. By empirically validating the challenges in manual and automated construction progress monitoring, this paper contributes to theoretical frameworks and existing literature. The findings of this research provide empirical evidence to support the identified challenges, enriching theoretical discourse and advancing the understanding of construction progress monitoring dynamics in the Sri Lankan context and will support the stakeholders in choosing a project monitoring technique. By shedding light on the unique challenges faced in this setting, the paper contributes to a deeper understanding of how cultural, regulatory, and technological factors influence monitoring practices. This knowledge expansion facilitates cross-contextual comparisons and strengthens the theoretical foundations of construction progress monitoring. Further, future researchers can use the findings of this study to introduce an innovative CPM technique that can overcome the identified challenges and obstacles.

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