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Research Article

Complementary Roles of Brand Familiarity and Brand Differentiability in BIM Software Purchase Decisions Among Selected Architectural and Construction Firms

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ABSTRACT

This research is about the predictive effect of Brand Familiarity and Brand Differentiability in Building Information Modeling (BIM) Software Purchase Decision of selected architectural and construction firms in the Philippines. A quantitative descriptive-predictive design was employed to collect data from 125 respondents involved in evaluating, selecting or using BIM software. The measurement of Brand Familiarity was based on awareness, recognition, prior exposure and reputation. Usability, cost, technical features and vendor support were measured as Brand Differentiability. Purchase intent, risk reduction and brand preference were used to measure the purchase decision. The data were analyzed using descriptive statistics, simple linear regression and multivariate linear regression. The findings revealed high levels of Brand Familiarity, Brand Differentiability & BIM Software Purchase Decision. Brand Familiarity was a significant predictor of Brand Differentiability and Brand Differentiability was a significant predictor of BIM Software Purchase Decision. When both Brand Familiarity and Brand Differentiability were considered simultaneously, they remained significant predictors of BIM Software Purchase Decision, implying that each of them contributed unique information to the model. The results indicate that the two constructs are complementary rather than substitutable: Brand Familiarity reflects the knowledge, recognition, and experience potential buyers have about a software brand, while Brand Differentiability reflects the qualities that distinguish software alternatives. Thus, BIM software purchase decisions may be better understood by considering both buyer familiarity and the distinguishing qualities of the software and its supporting services.

Keywords: *BIM software, Brand differentiability, Brand familiarity, Building information modeling purchase decision, Software evaluation*

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Introduction

The construction industry is rapidly embracing the digital world, with BIM playing a significant role in this transformation. But it's not just about making digital copies of buildings. BIM links project information and makes it accessible during the different phases of design, construction and project delivery. This has affected the way project participants work together especially in coordinating activities, sharing information and handling the increasing complexity of construction projects (Succar, 2009; Azhar, 2011). But technology isn't the sole reason for BIM adoption. Recent studies have shown that the adoption is influenced by the construction industry and organizational environment (Stojanovska-Georgievska et al., 2022; Chowdhury et al., 2024).

The study combines the technology adoption and consumer behavior perspectives to explain the evaluation of BIM software by potential users. The Technology Acceptance Model (TAM) (Davis, 1989) postulates that a technology is more likely to be accepted if it is perceived to be useful and relatively easy to use. Diffusion of Innovations theory provides further dimensions to demonstrate how knowledge, prior exposure and perceptions of an innovation may influence how it is considered and finally adopted (Rogers, 1995). The branding perspective is relevant too, as consumers do not evaluate products in isolation from what they know about a brand. The customer-based brand equity theory (Keller, 1993) explains how consumer responses are influenced by brand awareness and associations. These views together provide a basis for analyzing BIM software purchase decisions with two related, but distinct considerations. Brand Familiarity is how well potential customers know and recognize a software brand, while Brand Differentiability is the ability of potential customers to distinguish between one software offering and another based on usability, price, technical features, vendor support, and so on.

Although the adoption of BIM is increasing, it is not happening at the same rate for different countries and organizations and their levels of technology readiness. But new research shows this variation isn't just a matter of technology. Organizational support, user readiness,

implementation challenges and the broader economic and institutional context affect BIM adoption and application (Ahmed & Kassem, 2019; Alemayehu et al., 2022; Alhusban, 2026; Chowdhury et al., 2024; Farea et al., 2023; Olugboyega & Windapo, 2023; Roseli et al., 2024; Wang et al., 2024). Evidence from other organizational settings likewise indicates that digitalization can improve operational speed and accuracy while creating additional requirements for training, data management, and technical support (Andres et al., 2024). The Philippine AEC industry also provides a similar case where Mata et al. (2024) reported that BIM adoption is associated with technological and user-related factors. This means that the choice of a software is not determined by its functionality only. The second question becomes increasingly important as BIM is being integrated into professional practice. Therefore, not only will the firms be using BIM they will have many options to choose from, in terms of software. Here, knowledge of a software brand and how it differentiates itself from competing brands can influence the buying decision.

Most of the studies on BIM have focused on the factors that promote or hinder its adoption. The research mainly focused on technological requirements, organizational conditions, and implementation issues (Arayici et al., 2011; Chowdhury et al., 2024; Hao & Mohd-Nor, 2024; Herr & Fischer, 2019; Gu & London, 2010). Brand familiarity has been widely studied in relation to consumers and it is associated with consumer brand evaluation, brand confidence and purchase intentions (Campbell & Keller, 2003; Kent & Allen, 1994; Laroche et al., 1996). The exploration of these types of relationships has been relatively little explored for specialized professional software such as BIM. In particular, there is little research into familiarity with BIM software brands and attributes that make one software option different from another such as usability, cost, technical features, and vendor support. It expands the scope of inquiry. Do awareness and recognition of a BIM software brand and perception of meaningful differences between available alternatives constitute different but complementary considerations in software purchasing decisions?

This gap has resulted in the study focusing on Brand Familiarity and Brand Differentiability and BIM Software Purchase Decision among selected architectural and construction firms. Brand Familiarity is analyzed from the perspective of awareness, recognition, prior exposure and reputation. Brand Differentiability is analyzed from the perspective of usability, cost, technical features and vendor support. BIM Software Purchase Decision is analyzed in terms of purchase intent, risk reduction and brand preference. The study not only describes these constructs, but also investigates their relationships and determines to what extent Brand Familiarity and Brand Differentiability, individually and jointly, statistically predict BIM Software Purchase Decision. Therefore, the study aims to answer the following questions:

Specifically, the study seeks to determine (1) the profile of the selected architectural and construction firms based on the characteristics presented in the study; (2) the level of Brand Familiarity with BIM software in terms of awareness, recognition, prior exposure, and reputation; (3) the level of BIM Software Purchase Decision in terms of purchase intent, risk reduction, and brand preference; and (4) the level of Brand Differentiability in terms of usa-

bility, cost, technical features, and vendor support. Furthermore, the study determines (5) the extent to which Brand Familiarity statistically predicts Brand Differentiability; (6) the extent to which Brand Differentiability statistically predicts BIM Software Purchase Decision; and (7) the extent to which Brand Familiarity and Brand Differentiability jointly statistically predict BIM Software Purchase Decision.

The following null hypotheses are tested based on the specific questions of the study. (H₀1) Brand Familiarity does not have a significant effect on BIM Software Purchase Decision; (H₀2) Brand Differentiability does not significantly predict BIM Software Purchase Decision; and (H₀3) Brand Familiarity and Brand Differentiability do not simultaneously significantly predict BIM Software Purchase Decision.

Figure 1. Conceptual Model of the study Proposed relationships between Brand Familiarity, Brand Differentiability and BIM Software Purchase Decision. The independent variables are Brand Familiarity and Brand Differentiability and the dependent variable is BIM Software Purchase Decision. It provides a framework to explore the relationship between familiarity with BIM software brands and perceived attributes that differentiate these brands and organizational software purchasing decisions.

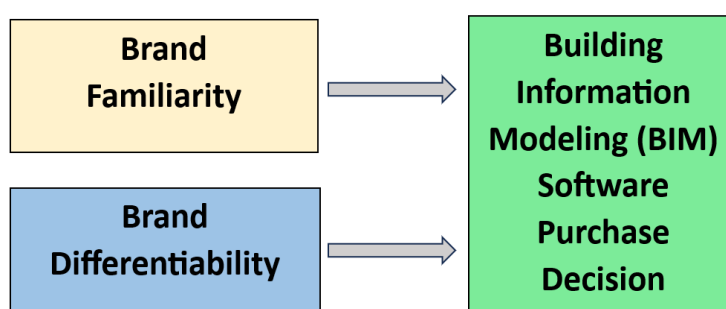


Figure 1. Conceptual Model of the Relationship Among Brand Familiarity, Brand Differentiability, and BIM Software Purchase Decision

Figure 1 shows that Brand Familiarity and Brand Differentiability are different but related issues when evaluating BIM software. Brand Familiarity is the degree to which potential buyers know, recognize, have been exposed to, and have a reputation for a BIM software brand. Brand Differentiability refers to the degree to which BIM software brands are perceived as differentiable in terms of usability,

cost, technical features and vendor support. The directional paths from these two constructs toward BIM Software Purchase Decision indicates that each is treated as a statistical predictor of purchase decision which is reflected through purchase intent, risk reduction and brand preference. The model therefore tests whether familiarity with a software brand and its perceived differentiating qualities

provide complementary information in explaining BIM software purchase decisions.

Materials and Methods

Research Design

This study used a quantitative descriptive-predictive research design in the study of Brand Familiarity, Brand Differentiability and BIM Software Purchase Decision of selected architectural and construction firms. The descriptive part was applied to present the profile of the participating firms and to determine the levels of Brand Familiarity, Brand Differentiability and BIM Software Purchase Decision based on its dimensions. The predictive section was used to test the statistical relationships between the study variables using regression analysis. Specifically, simple linear regression was used to determine the predictive relationships examined separately, whereas multiple linear regression was used to determine the joint predictive contribution of Brand Familiarity and Brand Differentiability to BIM Software Purchase Decision. The design was a nonexperimental study that focused on statistical prediction rather than establishing causal relationships between the variables.

Respondents

The study sample included representatives from 125 selected architectural and construction firms that were involved in the evaluation, selection or use of Building Information Modeling (BIM) software. These companies were based in the major urban centers of the Philippines, such as Metro Manila, Cebu and Davao. The purposive sampling technique was used to select respondents who have knowledge or experience in decision making in evaluating and buying BIM software. In this way the study was able to reach out to people whose job and expertise were directly related to Brand Familiarity, Brand Differentiability and BIM Software Purchase Decision.

Instruments

A structured questionnaire was used for the measurement of three main constructs (Brand Familiarity, Brand Differentiability and BIM Software Purchase Decision). A 5-point Likert scale was used to rate items. Brand Familiarity (awareness, recognition, prior exposure and reputation) was conceptualized on the basis of

concept of brand knowledge and familiarity. Brand awareness and brand image are fundamental components of brand knowledge (Keller, 1993); brand familiarity is linked to confidence, brand attitudes and purchase intention (Laroche et al., 1996). These perspectives provide a conceptual basis for measuring the respondents' familiarity with BIM software brands.

Brand Differentiability was assessed based on usability, cost, technical features and vendor support. Its measurement was based on technology-evaluation perspectives, particularly the importance of perceived usefulness and ease of use in technology systems evaluation (Davis, 1989), and on Keller's (1993) view that unique brand associations may influence responses toward competing brands. Laroche et al. (1996) provided support for BIM Software Purchase Decision through the constructs of purchase intent, risk reduction and brand preference by showing the relationships between brand familiarity, confidence, brand attitudes and purchase intention.

The internal consistency of the instrument was assessed using Cronbach's alpha. The obtained coefficients were .8758 for Brand Familiarity, .9087 for Brand Differentiability, and .9725 for BIM Software Purchase Decision, indicating high internal consistency across the three measures.

Data Collection

The structured questionnaire was distributed electronically through email and relevant professional networks to collect data. The data collection process took a period of eight weeks within which the respondents from the selected construction and architectural firms had enough opportunity to participate. Before filling in the questionnaire, respondents were informed about the purpose of the study and assured that their participation in the study was voluntary and their responses would be treated as confidential. Before the survey, ethical clearance and necessary permission from the institution were obtained.

Data Analysis

Data analysis employed descriptive and inferential statistical techniques appropriate to the research questions. The respondents and

their firms' profile was described using frequencies and percentages while the levels of Brand Familiarity, Brand Differentiability and BIM Software Purchase Decision were determined using means and standard deviations. The predictive analyzes were conducted using simple linear regression to find out the extent to which Brand Familiarity predicted Brand Differentiability and how much Brand Differentiability predicted BIM Software Purchase Decision. Then, a multiple linear regression was performed to examine the joint predictive contribution of Brand Familiarity and Brand Differentiability to BIM Software Purchase Decision. Statistical significance was assessed at the .05 level.

Ethical Considerations

The study was performed in accordance with the research ethical standards. Participants were informed of the purpose of the study and participated voluntarily and could refuse to participate or withdraw at any time

without penalty. Responses were combined and used for research purposes only and confidentiality was ensured by not attributing responses to individual respondents or to firms. The study also obtained the required ethical clearance and institutional permission before the data collection. The information obtained was treated responsibly and used only for the purpose of the study.

Results and Discussions

Profile of the Respondents and their Firm Size

Table 1 shows the profile of respondents by professional role and firm size. These characteristics set the stage for understanding the composition of the sample, and the professional and organizational contexts represented in the study. These characteristics are important to consider because there can be professionals in different roles and in firms of different organization sizes involved in the evaluation and purchase of BIM software.

Table 1. Respondent Profile by Professional Role and by Firm Size

Category	Subgroup	Frequency (n)	Percentage (%)
Professional Role	Architects	50	40%
	Engineers	38	30%
	Project Managers	25	20%
	Procurement Officers	12	10%
Firm Size	Small (<50 employees)	56	45%
	Medium (50–200 employees)	44	35%
	Large (>200 employees)	25	20%
Total Respondents	—	125	100%

Table 1 shows that the largest professional group was architects with 50 respondents (40%) followed by engineers (38, 30%), procurement officers (12, 10%) and project managers (25, 20%). The respondents were from firms of varying sizes; 56 respondents (45%) were from small firms (less than 50 employees), 44 (35%) were from medium sized firms (50–200 employees) and 25 (20%) were from large firms (more than 200 employees). Thus, the sample contained respondents from each of the four professional roles and each of the three firm-size categories that were included in the study.

The distribution shows that the majority of the respondents were architects and engineers, representing 70 % of the sample, and the

project managers and procurement officers, representing the managerial and procurement related functions. Similarly, 80% of the sample were small and medium-sized firms, and 20% were large firms. Therefore, the results should be interpreted in light of a sample dominated by architects and engineers and by respondents from small and medium-sized businesses rather than a balanced representation of the different professional roles and firm sizes.

The range of professional positions and firm sizes provides an appropriate organizational setting for the analysis of BIM software evaluation and purchase decisions. Existing studies demonstrate that the adoption and assessment of BIM takes place in organizational contexts where technological, individual and

organizational factors are interrelated and the perspectives of various professional participants matter for BIM related decisions (Chowdhury et al., 2024; Mata et al., 2024; Moreno et al., 2019). Importance of the size of the firm Organizational characteristics and resource capability can influence BIM adoption and implementation particularly for small and medium firms. The overall findings need to be viewed at the same time in the light of the larger representation of architects, engineers and smaller firms in the present sample. Hence, the profile of the respondents provides the context and scope for the forthcoming findings on Brand

Familiarity, Brand Differentiability and BIM Software Purchase Decision.

Brand Familiarity

Table 2. Level of Brand Familiarity with BIM software (Awareness, Recognition, Previous Exposure and Reputation). These dimensions reflect different routes through which respondents may be aware of BIM software brands, from knowing and recognizing a brand to having prior exposure to it and its reputation. The outcomes give an idea of the general level of familiarity of the respondents with the brands of BIM software.

Table 2. Mean Score and Interpretation of Level of Brand Familiarity

Level of Familiarity	Mean	SD	Interpretation
Awareness	4.160	0.700	High
Recognition	3.816	0.614	High
Prior Exposure	3.208	0.710	Moderate
Reputation	3.376	0.486	Moderate
Average	3.640	0.574	High

Legend:

4.21–5.00	Very High
3.41–4.20	High
2.61–3.40	Moderate
1.81–2.60	Low
1.00–1.80	Very Low

Overall, the results show a high score of Brand Familiarity ($M = 3.640$, $SD = 0.574$). Among the dimensions, awareness obtained the highest mean ($M = 4.160$, $SD = 0.700$), which is interpreted as high, followed by recognition ($M = 3.816$, $SD = 0.614$), which is interpreted as high. For reputation the mean was 3.376 ($SD = 0.486$). Prior exposure was the lowest mean with 3.208 ($SD = 0.710$). Both were interpreted as moderate. Thus, the respondents were highly familiar with BIM software brands in general, but the results were different across the different dimensions of familiarity.

The higher scores on awareness and recognition indicate that respondents are generally aware of and able to recognize BIM software brands in their professional environment. However, low levels of prior exposure and reputation suggest that awareness or recognition of a software brand does not necessarily translate into substantial direct experience with the brand or into equally strong reputation perceptions. This difference is consistent with the

notion that brand familiarity is based on acquired knowledge and experience, and can be of different intensities depending on the individual's experience with the brand (Alba & Hutchinson, 1987; Keller, 1993). In the case of BIM software, respondents may therefore be familiar with certain software brands through professional practice, education, demonstration, colleagues or market exposure even if their direct experience with those brands is still limited.

The findings imply that the mere visibility of a brand may be enough to generate awareness and recognition but not necessarily deep familiarity on the basis of experience and reputation. For BIM software vendors, that means the need to supplement brand visibility with opportunities for prospective organizational users to receive meaningful exposure to the software through demonstrations, training, trial use, technical support and other forms of direct engagement. This is consistent with research suggesting that familiarity can lead to

confidence and subsequent purchase judgments (Laroche et al., 1996) and that familiarity can reduce uncertainty in technology-mediated contexts (Gefen, 2000). In architecture and construction organizations the results also mean that brand recognition of BIM software should not be a substitute for a direct assessment of the suitability of a BIM tool to the organizational requirements. This underscores the significance of transitioning from awareness of a BIM software brand to having enough information and experience to make a meaningful assessment of it, given the relatively high awareness and recognition scores versus the

moderate prior-exposure and reputation scores.

Brand Differentiability

Table 3 presents the level of Brand Differentiability for BIM software in terms of usability, cost, technical features and vendor support. These dimensions are characteristics by which the respondents may compare a BIM software brand to others in the market when they are evaluating the alternatives. The results give an indication of the extent to which these differentiating attributes are perceived as relevant in the assessment of BIM software brands.

Table 3. Mean Score and Interpretation of Level of Brand Differentiability

Evaluation Consideration	Mean	SD	Interpretation
Usability	4.160	0.700	High
Cost	3.376	0.486	Moderate
Technical Features	4.160	0.700	High
Vendor Support	4.184	0.711	High
Average	3.970		High

Legend:

4.21–5.00	Very High
3.41–4.20	High
2.61–3.40	Moderate
1.81–2.60	Low
1.00–1.80	Very Low

The results indicate an overall high level of Brand Differentiability ($M = 3.970$). Among the four dimensions, vendor support obtained the highest mean ($M = 4.184$, $SD = 0.711$), interpreted as high. Usability and technical features obtained identical means ($M = 4.160$, $SD = 0.700$), also interpreted as high. Cost obtained the lowest mean ($M = 3.376$, $SD = 0.486$) and was interpreted as moderate. The findings therefore show that respondents perceived BIM software brands as highly differentiable overall, although the degree of differentiation varied across the specific dimensions.

Higher scores for vendor support and usability and technical features indicate that respondents differentiate BIM software brands most on the basis of features related to their practical use and to their ongoing implementation. Vendor support was the highest rated, indicating that services surrounding the software may be especially salient in respondents' comparisons of available brands. Likewise, the high

scores on usability and technical features suggest that perceived differences between alternatives include ease of working with the software as well as functional features. Cost was rated as interestingly only moderate. This is in line with the BIM adoption literature that technological and organizational conditions are important in the adoption and implementation of BIM (Arayici et al., 2011; Chowdhury et al., 2024; Gu & London, 2010; Herr & Fischer, 2019; Hua et al., 2024).

The findings imply that differentiating a brand in the BIM software market may be more than just price, and may be more dependent on the overall value offered by the software and its vendor. Therefore, BIM software vendors can increase their differentiation by improving customer service, creating technical capabilities that meet the needs of professionals, and providing reliable support before and after the purchase of the software. The lower relative rating of cost is not to say that price is not

important, but it does suggest that besides price, respondents also value the qualities associated with the effective and sustained use of the software. The findings suggest architectural and construction firms should assess competing BIM software brands on multiple dimensions rather than focusing predominantly on acquisition cost. Such an approach is especially relevant as BIM implementation involves technological as well as organizational requirements (Chowdhury et al., 2024; El Hajj et al., 2023; Gu & London, 2010; Nývlt, 2018).

BIM Software Purchase Decision

Table 4 shows the level of BIM Software Purchase Decision on purchase intent, risk reduction and brand preference. These dimensions reflect the respondents' purchasing orientation toward BIM software, such as their willingness to consider purchasing it, the importance of decreased uncertainty in their assessment, and the preference for particular software brands. The results provide a general indication on the strength of BIM software purchase decision among the respondents.

Table 4. Mean Score and Interpretation of Level of BIM Software Purchase Decision

Level of Purchase Decision	Mean	SD	Interpretation
Purchase Intent	4.216	0.725	Very High
Risk Reduction	4.200	0.718	High
Brand Preference	4.136	0.688	High
Average	4.184		High

Legend:

4.21–5.00	Very High
3.41–4.20	High
2.61–3.40	Moderate
1.81–2.60	Low
1.00–1.80	Very Low

The results indicate that the level of the BIM Software Purchase Decision is high ($M = 4.184$). Purchase intent was highest among the three dimensions with a mean ($M = 4.216$, $SD = 0.725$) of very high. The next variable was risk reduction with mean of 4.200 and standard deviation of 0.718 which was interpreted as high. The mean of brand preference was 4.136 with a standard deviation of 0.688 which was interpreted as high. The results thus show a consistently high purchase-related response on the three dimensions, with purchase intention being the strongest.

The purchase-intent score is very high. This shows a high reported likelihood of consideration of the purchase of BIM software by respondents. Moreover, the high scores in risk reduction and brand preference indicate that the decision making in purchase is not only about purchase intention, but also respondents are concerned about uncertainty reduction and preferences among the available software brands (Bearden & Etzel, 1982; Mitchell & Greatedorex, 1993). This pattern is consistent with Laroche et al. (1996) who found familiar-

ity and confidence are associated with purchase intention and Gefen (2000) who showed familiarity can contribute to trust and reduce uncertainty in technology-mediated environments. This is even more important in the BIM environment where software procurement usually includes financial commitments, training requirements, changes in workflows, technical compatibility and ongoing support.

The results reveal that the purchase decision of BIM software by the respondents is motivated by a blend of purchase willingness, perceived uncertainty reduction and brand preference. So software vendors may need to support purchase inducements with credible information, demonstrations, user experience, and ongoing support so prospective buyers can evaluate the software with greater confidence. High scores on purchase-related questions from architectural and construction firms emphasize the significance of ensuring that purchase intentions and brand preferences are supported by a systematic assessment of organizational requirements and the practical attributes of competing software alternatives.

This is especially relevant as familiarity may impact confidence and purchase intention (Laroche et al., 1996) but organizational software decisions include also technological and implementation considerations (Chowdhury et al., 2024). Therefore, a strong desire to buy a BIM software brand has to be balanced with its real fit to the firm's technical and operational needs.

Brand Familiarity and BIM Software Purchase Decision

Table 5 shows the simple linear regression analysis of Brand Familiarity as a statistical predictor of Brand Differentiability. This analysis provides an indication of the presence of statistically significant differences among the awareness of BIM software brands by the respondents and their perception of the brands' ability to be distinguished in the aspects of usability, cost, technical features and vendor support.

Table 5. Simple Linear Regression Analysis of Brand Familiarity as a Statistical Predictor of BIM Software Purchase Decision

Predictor	<i>B</i>	β	<i>t</i>	<i>F</i>	R^2	<i>p-value</i>
Brand Familiarity	0.913	0.832	16.602	275.63	0.691	< .001

Note. Dependent variable: Brand Differentiability. *B* = unstandardized regression coefficient; β = standardized regression coefficient; R^2 = coefficient of determination. The regression model was statistically significant, $F(1, 123) = 275.63, p < .001, N = 125$.

The results of the regression analysis suggest that Brand Familiarity is a significant predictor of Brand Differentiability ($B = .913, \beta = .832, t = 16.602, p < .001$). The overall regression model was statistically significant, $F(1, 123) = 275.63, p < .001$, accounting for 69.1% of the variance in Brand Differentiability ($R^2 = .691$). The positive value of regression coefficient indicated that the higher was the brand familiarity, the higher was perceived brand differentiability. So, the null hypothesis that Brand Familiarity is not significant to predict Brand Differentiability is rejected.

The high positive standardized coefficient ($\beta = .832$) indicates that the respondents who had more familiarity with the BIM software brands were likely to perceive clearer differences among the brands. The relationship appears to be conceptually reasonable, because familiarity is based on accumulated knowledge and exposure, which may provide individuals with a richer basis for discriminating among alternatives (Alba & Hutchinson, 1987; Keller, 1993). Familiarity may help potential buyers to identify differences in usability, technical features, cost and vendor support that are less obvious to buyers with limited knowledge or exposure to BIM software. However, the results are a statistical prediction relationship, not a

proof that Brand Familiarity causes Brand Differentiability, consistent with the non-experimental design of the study.

The results show that awareness of BIM software brands might have practical significance beyond the brand's recognition. As potential organizational buyers become better educated about the software brands available, they may be better able to distinguish meaningful differences among competing alternatives. For BIM software suppliers this means that increased exposure needs to be complemented by opportunities for potential users to learn about the software's unique qualities through demonstrations, training, trial use, technical information and direct product experience. The findings suggest that greater familiarity may help architecture and construction firms make more informed comparisons between BIM software alternatives, but that familiarity should be used in conjunction with systematic evaluation of software capabilities and organizational requirements. This distinction is significant because brand knowledge can influence how consumers react to brands (Keller, 1993), while BIM adoption involves broader technological and organizational factors (Chowdhury et al., 2024).

Brand Differentiability and BIM Software Purchase Decision

Table 6 shows the simple linear regression analysis of the statistical predictive power of Brand Differentiability on BIM Software Purchase Decision. The analysis considers the

extent to which the perceptions of differences between BIM software brands on usability, cost, technical features and vendor support are statistically related to the respondents' purchase decisions.

Table 6. Simple Linear Regression Analysis of Brand Differentiability as a Statistical Predictor of BIM Software Purchase Decision

Predictor	<i>B</i>	β	<i>t</i>	<i>F</i>	R^2	<i>p-value</i>
Brand Differentiability	0.899	0.827	16.287	265.28	0.683	< .001

Note. Dependent variable: BIM Software Purchase Decision. *B* = unstandardized regression coefficient; β = standardized regression coefficient; R^2 = coefficient of determination. The regression model was statistically significant, $F(1, 123) = 265.28, p < .001, N = 125$.

Brand Differentiability was a significant predictor of BIM Software Purchase Decision, $B = .899, \beta = .827, t = 16.287, p < .001$ (Table 3). The overall regression model was statistically significant, $F(1, 123) = 265.28, p < .001$, and accounted for approximately 68.3% of the variance in BIM Software Purchase Decision ($R^2 = .683$). Positive coefficient means that the higher the Brand Differentiability perception, the higher the score on BIM Software Purchase Decision. Thus, null hypothesis that Brand Differentiability does not significantly predict BIM Software Purchase Decision is rejected.

The standardized coefficient ($\beta = .827$) indicates that Brand Differentiability is strongly positively predictive of BIM Software Purchase Decision. Those who found more differences between BIM software brands for usability, cost, technical features and vendor support, also reported higher purchase intent, risk reduction and brand preference. This pattern is in line with the general BIM literature that emphasizes the significance of technological and organizational aspects in the adoption and evaluation of technologies (Gu & London, 2010; Chowdhury et al., 2024). This finding indicates that besides the availability of BIM software, organizational buyers may also respond to the qualities on the basis of which one software alternative can be distinguished from another. However, the study was nonexperimental, so the result suggests statistical prediction rather than causation.

The results suggest that the ability of BIM software brand to be differentiated by

meaningful product and service attributes may be important in organizational purchase decisions. For BIM software vendors, therefore, differentiation should be more than brand visibility, but attributes that potential buyers can assess, specifically usability, technical features, vendor support and value relative to cost. The result offers a basis for architectural and construction firms to compare software alternatives according to well-defined criteria, rather than relying mainly on brand recognition. Such an assessment may allow firms to assess whether the qualities that distinguish a particular software brand are in line with their technical, operational and organizational requirements. The strong predictive association also empirically lends support to the notion that Brand Differentiability should be treated as a separate construct from Brand Familiarity and not simply as a reduction of software purchase decisions to familiarity.

Brand Familiarity, Brand Differentiability, and BIM Software Purchase Decision

Table 7 Multiple linear regression analysis of Brand Familiarity and Brand Differentiability as simultaneous statistical predictors of BIM Software Purchase Decision. Unlike the earlier simple regression analyzes, this model estimates the unique contribution of each predictor after controlling statistically for the other and estimates the extent to which the two predictors, taken together, account for variation in BIM Software Purchase Decision.

Table 7. Multiple Linear Regression Analysis of Combined Brand Familiarity and Brand Differentiability as a Statistical Predictor of BIM Software Purchase Decision

Predictor	<i>B</i>	β	<i>t</i>	<i>F</i>	<i>R</i> ²	<i>p</i> -value
Brand Familiarity	0.510	0.464	5.302	175.94	0.748	< .001
Brand Differentiability	0.469	0.431	4.921	265.28	0.743	< .001

Note. Dependent variable: BIM Software Purchase Decision. *B* = unstandardized regression coefficient; β = standardized regression coefficient. The overall regression model was statistically significant, $F(2, 122) = 175.94$, $p < .001$, $R^2 = .743$, adjusted $R^2 = .738$, $N = 125$.

The multiple regression model was statistically significant, $F(2, 122) = 175.94$, $p < .001$, explaining approximately 74.3% of the variance in BIM Software Purchase Decision ($R^2 = .743$, adjusted $R^2 = .738$). Brand Familiarity was a significant positive predictor ($B = .510$, $\beta = .464$, $t = 5.302$, $p < .001$) and Brand Differentiability was a significant positive predictor ($B = .469$, $\beta = .431$, $t = 4.921$, $p < .001$). The standardized coefficient for Brand Familiarity was slightly greater than that for Brand Differentiability, but both were significant unique contributors to the model. Therefore, the null hypothesis, that Brand Familiarity and Brand Differentiability do not jointly significantly predict BIM Software Purchase Decision is rejected.

The results show that Brand Familiarity and Brand Differentiability still have significant relationship with BIM Software Purchase Decision when taken together. The standardized coefficient for Brand Familiarity ($\beta = .464$) is slightly higher than the standardized coefficient for Brand Differentiability ($\beta = .431$) suggesting a slightly larger unique statistical contribution to this particular model, but the relatively close coefficients show that both constructs contribute meaningfully. This finding is consistent with evidence that the relative contribution of predictors can change when they are considered simultaneously, making multiple regression useful for distinguishing their unique contributions within a combined model (Egera et al., 2026). This implies that awareness and recognition of a BIM software brand and the ability to distinguish it from competing alternatives are conceptually related but separate purchase considerations. Familiarity provides a brand with a knowledge base that is recognizable and understood, whereas differentiability provides a basis of comparison for its usability, cost, technical features and vendor support against competing alternatives. This interpretation is in agreement with Keller's (1993)

proposition that brand knowledge influences consumer responses and with the BIM literature that emphasizes the importance of technological and organizational factors in software adoption (Chowdhury et al., 2024). But this study is nonexperimental, so these results are statistical prediction, not causation.

The results suggest that together familiarity and differentiation explain the decision to buy the BIM software better than the factors analyzed separately. It is still important for software vendors to build a well-known and familiar brand, but familiarity per se may not be enough. Potential organizational buyers need to be able to identify substantive qualities that distinguish the software from alternatives. This points to a two-pronged approach: building market familiarity through sustained professional engagement and clearly articulating differentiators including usability, technical competence, cost value proposition and vendor support. For architecture and construction firms, the findings are similar in that familiarity can be a starting point for considering a software brand, and differentiation can help compare alternatives. The combined model has a high explanatory power ($R^2 = .743$) which also suggests that these two constructs jointly explain a significant proportion of the variance in the purchase-decision scores of the respondents. The other 25.7% can be explained by other factors not included in the model.

Summary of Findings

The study revealed different professional roles of the respondents and different sizes of the firms they worked for and were in the architectural and construction sector. Overall, they exhibited a high level of Brand Familiarity, particularly in awareness and recognition, while prior exposure and reputation were comparatively moderate. They also reported a high level of Brand Differentiability, with vendor

support, usability and technical features emerging as stronger bases for distinguishing BIM software brands than cost.

The results also showed a high level of BIM Software Purchase Decision. Purchase intent was very high as was brand preference and risk reduction. The regression analyzes showed that Brand Familiarity was a significant predictor of Brand Differentiability, indicating that the more familiar respondents were with BIM software brands, the more clearly they perceived the differences among the brands. In turn, Brand Differentiability was an important predictor of BIM Software Purchase Decision, with higher perceived differences among BIM software brands being associated with stronger purchase decisions.

Finally, the joint effect of Brand Familiarity and Brand Differentiability significantly predicted BIM Software Purchase Decision, with both constructs making significant contributions when examined together. The results thus point to the fact that familiarity and differentiability are related but separate issues in the buying of BIM software: familiarity provides a basis for knowing and recognizing the brands of software; differentiability enables the respondents to differentiate between the options available. Taken together, these findings support the proposed framework linking Brand Familiarity, Brand Differentiability, and BIM Software Purchase Decision.

Summary of Implications

The results show the importance of Brand Familiarity in the differentiation of BIM software brands by the respondents. Familiarity may provide knowledge and recognition needed to identify meaningful differences among the alternatives available. This means that building awareness for BIM software providers must be matched with opportunities for prospective users to gain more knowledge and experience of the software.

The results also showed that Brand Differentiability is significant in BIM Software Purchase Decision. Respondents distinguish software alternatives especially regarding usability, technical features and vendor support while cost is less emphasized. This shows that BIM software vendors might want to emphasize clear, meaningful differentiation in their

products rather than relying mostly on brand awareness or price.

Finally, the combined results indicate that Brand Familiarity and Brand Differentiability should be considered jointly to understand BIM software purchase decisions. Familiarity can help establish the pool of software brands that get considered for architecture and construction firms, and differentiability can provide a basis for judging which alternative better matches organizational requirements. For software vendors it suggests that developing a familiar brand and meaningful distinctions from competitors may be complementary in strengthening the brand's position in organizational purchase decisions.

Limitations of the Study

The study is confined to a select group of architectural and construction firms and may not be reflective of BIM software buying practices in the wider construction industry or in other professional environments. Use of purposive sampling and responses to self-report questionnaires may also limit the generalizability of findings and may be biased by respondents' perceptions and response tendencies. Moreover, the nonexperimental and cross-sectional design establishes statistical predictive relationships but does not demonstrate causality while the model is limited to Brand Familiarity and Brand Differentiability and does not account for other factors that may contribute to BIM Software Purchase Decision as organizational resources, compatibility requirements, management support and actual software experience.

Future Research Directions

Future research can expand the study by examining Brand Familiarity, Brand Differentiability, and BIM Software Purchase Decision in a broader range of architectural and construction firms, geographic areas, and professional groups to ascertain whether the relationships found in this study can be generalized to other contexts. Researchers may include other factors such as organizational resources, software compatibility, management support, perceived value and actual software experience to construct a more comprehensive explanation of BIM software purchase decisions. Longitudinal

or comparative studies can further investigate the evolution of familiarity, perceptions of differentiation and purchase decisions over time and whether these relationships differ among different BIM software brands, firm sizes or stages of BIM adoption.

Conclusion

The study concluded that Brand Familiarity and Brand Differentiability are different but complementary considerations in understanding BIM Software Purchase Decision. Brand Familiarity is approached mostly from the buyer's existing knowledge and experience with a software brand through awareness, recognition, prior exposure and reputation. Brand differentiation, in contrast, starts with the attributes that distinguish the software and its offering from alternatives—especially in terms of usability, cost, technical features, and vendor support—and then moves to the decision. The two constructs do not negate or substitute each other, but provide different but related insight into the evaluation of BIM software. This interpretation is supported by the finding that familiarity predicts differentiability significantly and that both constructs continue to make significant contributions when considered together in predicting purchase decision.

The findings therefore suggest that knowing the software and evaluating what the software offers are both relevant to purchase decisions. Familiarity may enable prospective buyers to recognize and understand available BIM software brands, while differentiability provides the basis for determining how one alternative differs from another. A familiar software brand may enter the buyer's consideration more readily, but its usability, technical capabilities, cost-related value, and vendor support remain important when alternatives are compared. Conversely, strong software qualities may have limited decision value when prospective users lack sufficient familiarity to recognize and evaluate them. The relationship between the two constructs therefore points toward a purchase process in which user experience and software qualities can reinforce rather than displace one another.

In sum, the study broadens the understanding of BIM software purchases beyond a binary choice between brand familiarity and quality-

based software differentiation. Informed software selection for architecture and construction firms may require both adequate familiarity with available brands and systematic evaluation of the qualities that distinguish them. The implication for BIM software providers is also complementary: in addition to building a recognizable and familiar brand, it should also develop and communicate meaningful software and service qualities. BIM Software Purchase Decision is therefore better understood within the scope of this study as comprising both what buyers know and experience about the brand and what they perceive the software itself to offer.

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