2010
2011

FACULTY OF SCIENCES

Master of Statistics: Biostatistics

Masterproef

Exploring differences in patient safety subcultures in Belgian hospitals

Promotor :
Prof. dr. Marc AERTS
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Master Thesis nominated to obtain the degree of Master of Statistics , specialization Biostatistics

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Acknowledgements

I would like to thank my supervisors, Prof. dr. Marc Aerts, Dr. Ward Schrooten and Mevrouw Annemie Vlayen for their constant advice and direction in the writing of this thesis.

I would also like to thank all my classmates for their constant help and encouragement, but more especially my group members: Madona, Henry and Thembile, from whom I learnt a lot through the many discussions we had.

My deepest appreciation go to all my family members for the love they have shown me all through the two years I have been away from them, and more especially to my lovely daughters, Lynda and Chantal to whom I have been a "telephone mum" for such a long time.

Finally, I thank the Almighty God for making all this possible.

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Universiteit Hasselt

September 12, 2011

Abstract

Objectives: The purpose of this study is to explore patient safety culture differences in 90 Belgian acute hospitals; to understand workers' perceptions of safety culture and ways in which culture varies among hospitals and by work area and discipline. Furthermore, we wish to check if there are individual, unit or hospital related factors influencing differences in safety culture.

Research Design: The Hospital Survey on Patient Safety Culture (HSPSC) was distributed organization-wide in 180 Belgian hospitals participating in the federal program on quality and safety between 2007 and 2009. The HSPSC measures safety culture on 12 dimensions, including ten safety dimensions and two outcome dimensions, and is designed to measure staff perceptions on patient safety issues, medical errors and event reporting. The scores were expressed as the total and average of positive answers towards patient safety for each dimension. Only the outcome dimension "over all perception of patient safety" has been considered in this report.

Methodology: The survey measured safety culture perceptions and worker and job characteristics of hospital personnel. We calculated and compared the Percent of Positive Responses (PPR) consistent with a culture of safety among hospitals, work areas, and disciplines. In addition, a linear mixed model (LMM) as well as a Generalized Estimating Equations (GEE) model were fitted to see the differences between working units and professional background, as well as to find what other individual, unit or hospital related factors that influence differences in safety culture.

Results: Overall, 58.5% of responses were consistent with a positive safety culture. Patient safety culture differed by hospital and among and within work units and professions. Emergency department personnel perceived the worst safety culture while diagnostics perceived the best. Nurses perceived the lowest probability of overall perception of patient safety and the physicians the highest.

Conclusions: Differences among and within hospitals suggest that strategies for improving safety culture and patient safety should be tailored for work areas and disciplines.

Key words: Generalized Estimating Equations, Linear Mixed Model, Patient safety culture, Percent Positive Response, Profession, Work unit

Contents

1 Introduction

1.1 Background

Safety culture refers to the beliefs, values and attitudes of safety shared by all members of an organization. The culture of an organisation consists of the shared norms, values, behaviour patterns, rituals and traditions of the employees of an organization. These shared values are reflected in the day to day operations of the organization. (Schein, 1985). A positive safety culture guides much discretionary behaviour of healthcare professionals toward viewing patient safety as one of their highest priorities (Nieva and Sorra, 2003). Patient safety is an important component of healthcare quality. Several studies in various countries have shown that 2.9% to 16.6% of patients in acute care hospitals experience one or more adverse events and approximately 50% of the adverse events are judged to be preventable (Brennan, *et al.*, 1991). It is believed that to improve quality and safety in healthcare, hospitals have to create a patient safety culture among their staff besides making structural interventions. The Institute of Medicine states that if there is a safety culture where adverse events can be reported without people being blamed, they have the opportunity to learn from their mistakes and it is possible to make improvements in order to prevent future human and system errors, and thus promoting patient safety (Institute of Medicine, 2000).

Patient Safety is receiving growing attention in Belgium. A five year program (2007-2012) was launched to implement quality and patient safety initiatives in the acute, psychiatric and long term care hospitals. In 2007, the federal contract was signed by 80 % (n=164) of the hospitals, including 97 acute hospitals, 52 psychiatric hospitals and 15 long term care hospitals. The Belgian government provides a framework for implementing quality and safety strategies with attention to structure (how care is organized), processes (what is done by healthcare providers) and outcome measurement (the healthcare results achieved), according to Donabedian's trilogy. (Federal contract on quality and patient safety in Belgian hospitals, 2007-2008).

One of the main priorities in the federal program is developing a culture of safety. Understanding safety culture is seen as a key component in improving patient safety in Belgian hospital settings. During the first program year (2007-2008), 158 hospitals completed a hospital-wide measurement of the safety culture using the Hospital Survey on Patient Safety Culture (HSPSC). (Brennan, *et al.*, 1991). During the second program year (2008-2009), 22 other hospitals entering the federal patient safety program assessed the safety culture. In total, 88% of the Belgian hospitals (180 out of 205 hospitals) applied the HSPSC to measure the hospital wide safety culture. The federal government has organized a second measurement in 2011 in order to track changes in patient safety culture over time and evaluate the impact of specific safety interventions.

In many other countries the HSPSC is used to measure safety culture and previous research has shown that the instrument is psychometrically sound.(Bodur and Filiz, 2010). The instrument has also been tested to determine the most appropriate level -individual, unit and hospital level- for interventions aimed at improving the culture of patient safety. The unit level appears to be the dominating level for the clustering of responses to the dimensions, which would confirm that the HSPSC measures group values of culture and not just individual attitudes.(Smits, *et al.*, 2009). Previous Belgian research suggested differences between professional subgroups, although no representative conclusions could be made for the Belgian hospital sector (Hellings, *et al.*, 2010).

One dimension along which culture can vary within hospitals is by work area, such as the Pediatrics or intensive care unit (ICU). Previous work suggests that measuring safety culture of work areas can identify important opportunities for improvement.(Pronovost, *et al.*, 2003). Research has also shown that the safety culture of particular types of work areas varies across institutions and within institutions (Cooper, *et al.*, 2008). One question that arises when considering variations across work areas is the extent to which safety culture is related to the level of intrinsic hazard associated with work done in different areas. Previous literature supports the view that there could be variations in safety culture that are related to the pace and complexity of work performed in different work areas. For example, greater effort to overcome safety hazards in more intrinsically hazardous work areas could result in better safety culture in these areas, as has been demonstrated in anaesthesiology (Huang, *et al.*, 2007). Alternatively, more intrinsically hazardous work areas may not yet have made sufficient advances towards improving safety culture given their level of intrinsic risk. Although these hypotheses have been developed, they have not been directly tested in empirical research. Research has also examined safety culture perceptions among personnel by discipline. In general, physicians demonstrated more positive perceptions of safety culture than nurses and other clinical personnel. In one study, ICU physicians rated collaboration and communication with nurses more positively than did the nurses themselves, who reported difficulty speaking up, disagreements not appropriately resolved, and poor receptivity of their input into decision-making. However, other studies have found no difference between physicians and nurses (Makary, *et al.*, 2006) or more positive perceptions among nurses (Pronovost, *et al.*, 2003). One reason for these discrepancies may be that prior investigations have studied disciplines in different work areas and across limited numbers of safety culture dimensions. In order to formulate actions for improvement, it is important for hospitals to assess their baseline scores for the existing safety culture and determine areas of priority. This study describes the survey results of the acute hospitals which voluntarily submitted their data for comparison to other hospitals. Results of these analyses can provide additional information on the common strengths or areas that need improvement.

1.2 Objectives

The main objective of the present study is to explore ways in which safety culture varies among 90 Belgian acute hospitals and by characteristics of hospital workers, their work areas and their professions. Examined are results from a survey that measured healthcare workers' perceptions of safety culture across 12 dimensions to assess (1) whether there is a significant variation in safety culture based on professional background and working units in the hospital, (2) variation in patient safety culture within and across hospitals (3) whether there are other factors, that is, hospital (eg language spoken) and individual characteristics (eg experience, working hours) that may influence the patient safety culture.

2 Data

Data for this study were obtained from responses to the HSPSC**,** distributed anonymously to all individuals working in direct or indirect interaction with patients. The HSPSC was distributed organization-wide in 180 (88%) Belgian hospitals participating in the federal program on quality and safety in 2007-2009. A first group of 158 hospitals initiated the safety culture assessment in 2007-2008, while 22 other hospitals started up one year later. Through a contract with the federal authorities, participating hospitals (in their first contract year) committed to measure safety culture within the entire organization. Hospitals were free to distribute the survey electronically or paper based. Participating hospitals were invited to submit their data to a research database created by Hasselt University, a neutral academic institute. The database is not accessible for the governmental authorities and was developed to allow hospitals to compare their data to other hospitals and to provide data to hospitals to facilitate internal assessment and learning in the patient safety improvement process. The HSPSC included 42 items capturing features of safety culture considered important in related literature. Four additional items captured information on work area, patient safety grade, number of events reported and the respondent's back ground information about how long they have worked in the hospital and their current work area, how many working hours per week, their position, if they have direct interaction or contact with patients and how long they have worked in their current profession. Other variables recorded were the year and language. All the 42 safety culture items in the HSPSC used a 5-point Likert scale ranging from "strongly disagree" (1) to "strongly agree" (5) with a midway point of "neither" (3) and for some questions ranging from "never" (1) to "always" (5) with a midway point of "sometimes" (3). The 42 items were combined to create 12 dimensions, including ten safety dimensions and two outcome dimensions as shown in Table 1. For each respondent, a total score on each dimension was calculated and then the average score also calculated according to the number of questions in the dimension. Furthermore, the average score was dichotomised as positive (1) if it's greater than 3 and negative (0) if it is less than or equal to 3. In this report, only one of the dimensions ie "Overall perceptions of patient safety" will be used as the response variable.

The data has a 3-level structure at Hospital at the first level, work units at the second-level and individuals at the third level, therefore, scores from individuals in the same cluster are expected to be correlated.

It is not unexpected that there are missing observations in the dataset. The missingness may be due to the fact that the respondents did not feel comfortable responding to some questions or did not feel safe enough to reveal for example their profession or work unit since the questions are asking for their opinion or perception of patient safety. These missing observations pose additional challenges to the analysis and will be taken into account during the analysis.

Table 1: Safety and outcome dimensions

	Safety dimensions
D1	Supervisor/manager expectations and actions promoting safety
D2	Organizational learning–continuous improvement
D3	Teamwork within units
D4	Communication openness
D5	Feedback and communication about error
D6	Nonpunitive response to error
D7	Staffing
D8	Management support for patient safety
D9	Teamwork across units
D10	Handoffs and transitions
	Outcome dimensions
O1	Overall perceptions of patient safety
O2	Frequency of events reported

3 Methodology

3.1 Exploratory Data Analysis

We computed Percentage Positive Response (PPR) for each Profession, Work Unit and Hospital language. PPR reflects the percentage of positive responses (ie “Agree” and “Strongly agree”) to positively worded items or negative responses (ie “Disagree” and “Strongly disagree”) to negatively worded items. These percentages were computed as the percentage of all responses received. Three work areas considered of greater intrinsic hazard, based on observation and understanding of prior literature (eg Leape, *et al.*, 1991), are the Emergency Department (ED), Intensive Care unit (ICU), and Operating Theatre (OT) and the ones with less intrinsic hazard are Psychiatry, Pediatrics and Revalidation. Their PPR are compared with each other and also with all other work units. Likewise, the Professions considered to be of interest ie the Nurses, Physicians and Pharmacist are compared with each other and also with all other professions. Although safety culture is viewed as a multidimensional construct, we also calculated average PPR for the response variable as a summary statistic, which we refer to as “safety culture overall.” More so, the average scores for each Profession and Work unit within hospitals were computed and the differences and variability shown by use of box plots.

3.2 Missing Data Concepts

To incorporate missingness into the modeling process, the analyst must consider the underlying process that may have led to the missing data. Little and Rubin (1987) and Rubin (1987) distinguish between basically three missing data mechanisms that are discussed in Section 3.2.1., 3.2.2, and 3.2.3.

3.2.1 Missing Completely At Random

An observation is said to be *missing completely at random* (MCAR) if missingness is independent of both the observed and unobserved data, i.e. the probability of an observation being missing is independent of the response. Hence, the data can be analysed as though the pattern of missing values were predetermined. Under MCAR, various statistical methods, i.e. the frequentist, likelihood or Bayesian procedures can be performed ignoring the process that generated the missing values (Molenberghs and Verbeke, 2005). Although MCAR is convenient given the simplicity of ignoring the missingness, it is not applicable in many situations.

3.2.2 Missing at Random

Given the observed data and covariates, no additional information is contained in the missing data; this mechanism is referred to as *missing at random* (MAR). This implies that the probability of an observation missing is conditionally independent of the unobserved data given the values of the observed data and covariates (Molenberghs and Verbeke, 2005).

Under this mechanism, analyses based on the direct likelihood are valid under both the linear and generalized linear mixed model. However, frequentist methods such as the Generalized Estimating Equations (GEE) for discrete longitudinal data analysis are not valid and there is a need for modification through the Weighted Generalized Estimating Equations (WGEE). The assumption of MAR cannot readily be verified.

3.2.3 Missing Not at Random

When both assumptions of MCAR and MAR do not hold, the missingness is assumed to be *missing not at random* (MNAR). The probability of a measurement being missing depends on unobserved data and no simplification of the joint distribution of the full data is possible (Molenberghs and Verbeke, 2005). Inferences can only be made by making further assumptions, about whether the observed data alone carry no information, but the degree to which this is possible in practice varies greatly. Such models can be formulated within each of the three main families: selection, pattern-mixture, and shared parameter models.

3.3 Direct Likelihood

In general, likelihood based methods can be applied to incomplete data after deletion (e.g. CC) or imputation of the missing observations. Since missing values are no-longer present in the set of complete cases or in the imputed dataset, thus likelihood approaches are based on the full-data likelihood of the complete data. In contrast, for incomplete longitudinal or clustered data, any method within a likelihood framework would require working with the observed-data likelihood and this is called direct likelihood. A direct likelihood is a method that can be implemented under MAR. This method does not require imputation or deletion of the missing data. This is due to the fact that missing information will not contribute to the estimation of parameters. This method is restricted to fully likelihood approaches such as Linear mixed model (LMM). This LMM involves random effects which represent the variability in the subject-specific intercepts and slopes not explained by fixed effects.

3.4 Multiple Imputation

Multiple imputation (MI) was formally introduced by Rubin (1987). This technique replaces each missing value with two or more acceptable values representing a distribution of possibilities. The missing values are filled in m times to generate m complete data sets. These are generated from a plausible model which is based on a plausible set of parameters drawn from a sampling distribution of the parameter estimates. The m values are ordered in a sense that the first components of the vectors when substituted for the missing values result in one data set, the second components also result in a second data set, and so forth. These imputed values are stored in an auxiliary matrix with one row for each missing value and m columns. These m complete data sets are analyzed by using standard procedures. Results from the analyses are combined for the inference. This process results in valid statistical inferences that properly reflect the uncertainty due to missingness, that is, valid confidence intervals for parameters. (Rubin, 1987).

SAS v9.2 offers two procedures for multiple imputation and analysis of imputed data sets: PROC MI/PROC MIANALYZE. One of the complexities in using SAS for multiple imputation is the way it handles class variables and the methods for imputation required for imputation with class variables. The general idea is that one must have a monotone missing data pattern for imputation using class variables. This often requires a 2 step imputation process where the first step imputes just enough missing data to produce a monotone missing data pattern and then the 2^{nd} imputation fills in the remaining missing data using an appropriate method for the types of variables to be imputed. Five imputations are used in this study.

Therefore, after studying the missing patterns, the very first step is to use the Markov Chain Monte Carlo (MCMC) method to impute enough data to achieve a monotone missing data pattern. The second step imputes the remaining missing data on the continuous variables by use of the monotone regression and on the categorical variables by use of the monotone logistic.

Once the imputations are complete, the imputed data sets are then analysed with the appropriate standard methods and finally use of PROC MIANALYZE to analyse the combined fully imputed data. SAS has the ability to read in the correct information from the imputed data sets and thus account for the clustered nature of the data as well as the variability introduced by the imputation process.

3.5 The Linear Mixed Model

Mixed modeling has become a major area of statistical research, including work on computation of maximum likelihood estimates, non-linear mixed effect models and missing data in mixed effects models. Mixed models are applied in many disciplines where multiple correlated measurements are made on each unit of interest or where measurements are made on clusters of related statistical units. They are prominently used in research involving human and animal subjects in fields ranging from genetics to marketing, and have also been used in industrial statistics.

As with all statistical problems, the method to use in data analysis depends on the type of data at hand. Perhaps the easiest data to work with due to the availability of extensive methods for analysis, especially in software implementation, is the continuous type of data. This stemmed from the fact that with continuous data, even if not normally distributed, transformations to attain normality are available and henceforth, the elegant properties of the normal distribution can be used. A nice property also of normally distributed data is that, integrating the mixed model over the random effects produces a marginal model. As such, regression parameter estimates of the Linear Mixed Model have marginal interpretation and the random effects contribute in a simple way to the variance-covariance structure (Verbeke and Molenberghs, 2000).

3.5.1 Model Specification

Specifying a linear mixed model for normal data, requires a two-stage hierarchical linear model where at stage one, the within subject (or cluster) observations is being modelled followed by the random regression coefficients modelling at stage two. The model with a single outcome, *r*, has the general structure below:

$$\begin{cases} \boldsymbol{Y}_{r,i} = \boldsymbol{X}_{r,i}\boldsymbol{\beta_r} + \boldsymbol{Z}_{r,i}\boldsymbol{b}_{r,i} + \boldsymbol{\varepsilon}_{r,i}, \qquad i = 1, \dots, m \\ \boldsymbol{b}_{r,i} \sim N(\boldsymbol{0}, D) \\ \boldsymbol{\varepsilon}_{r,i} \sim N(\boldsymbol{0}, \Sigma_i) \\ \boldsymbol{b}_{r,1}, \dots, \boldsymbol{b}_{r,m}, \boldsymbol{\varepsilon}_{r,1}, \dots, \boldsymbol{\varepsilon}_{r,m} \text{ are independent} \end{cases} \tag{1}$$

And $E(\boldsymbol{Y}_{r,i}) = \boldsymbol{X}_i\boldsymbol{\beta}$, $cov(\boldsymbol{Y}_{r,i}) = \boldsymbol{Z}_i D \boldsymbol{Z}_i{}' + \sigma^2 \boldsymbol{I}_{n_i} = \boldsymbol{Z}_i D \boldsymbol{Z}_i{}' + \boldsymbol{\Sigma}_i = \Omega_{\mathrm{i}}$

The vector $\boldsymbol{Y}_{r,i} = (Y_{r,i1}, Y_{r,i2}, \dots, Y_{r,in_i})'$ is an n_i-dimensional vector of all repeated measurements for the *i*th subject (or cluster). The matrix $\boldsymbol{Z_i}$ is the within-subject design matrix of order $n_i \ x \ q$, the vector $\boldsymbol{\beta}_r$ is a $p \ x \ r$ vector of fixed population parameters and $\boldsymbol{b}_r$, the random effects.

When subject- or cluster-specific profiles have cluster-specific intercepts as well as slopes, the resulting model is generally known as having random slopes (or random coefficients), e.g. in longitudinal studies where intercept and slope coefficients are specific to each time series. However, when all variability in cluster-specific slopes can be ascribed to fixed effect differences, the random slopes can then be omitted from the model, resulting to the so-called random-intercepts (error components or variance components) model. In that case, it would be assumed that there is a constant overall variance and a constant correlation within subject/cluster (Fahrmeir, and Tutz, 2001).

3.5.2 Covariance Structure

To obtain Maximum Likelihood (ML) or Restricted Maximum Likelihood (REML) parameter estimates for $\boldsymbol{\beta_r}$ and $\boldsymbol{b}_{r,i}$ under normality, pre-specification of the covariance structure (D and $\boldsymbol{\Sigma}_i$) is important. In general, there is little difference in the parameter estimates of models using different covariance structures, while there are often large differences in the estimated standard errors. It is thus advisable, when fitting a mixed linear model to a data set, to explore the covariance structure of the data by comparing several linear mixed models (Timm, 2002). Some of the frequently used covariance structures are; unstructured, simple, variance components, and compound symmetry. In unstructured covariance matrix, observations within a cluster are assumed to be correlated differently or have different variances or covariances. In the simple and variance components (VC), each random effect has a different variance component. Lastly, in the compound symmetry structure, all observations within the same cluster are assumed to have a constant correlation, but between cluster are also constant, however different from within cluster (Verbeke and Molenberghs, 2000). In this study, the unstructured covariance matrix has been used.

3.5.3 Model Assumptions

Recall that the model in (1) makes two main sets of assumptions. First, we assume that the model errors are normally distributed with mean zero and constant variance and that they are independent. Gregoire, Schabenberger, and Barret (1995) suggest using studentized residuals for investigating assumptions regarding the model errors where the studentized residual for the jth observation in the ith cluster is $e_{ij}^{c,stud} = e_{ij}^{c}/\sqrt{\widehat{Var(e_{ij}^{c})}}$

Where $\sqrt{\widehat{Var(e_{ij}^{c})}}$ is the estimated standard error of e_{ij}^{c}. A box plot of these residuals is plotted for each of the hospitals to check if their mean is zero and if their variance is constant. In addition a normal Q-Q plot of the studentized residuals is produced to check the normality assumption.

The second set of assumptions concerns the random effects. They are assumed to each be normally distributed with mean zero and constant variance. To check normality of random effects, Lange and Ryan (1989) proposed creating weighted normal quantile plots of standardized linear combinations of the random effects. However, since the linear combinations are functions of the random effects as well as of the error terms, these normal quantile plots can only indicate that these linear combinations do not have the distribution one expects under the assumed model, but they cannot differentiate a wrong distributional assumption for the random effects or the error terms from a wrong choice of covariates. This suggests that non-normality of the random effects can only be detected by comparing results obtained under the normality assumption with results obtained from fitting a model with relaxed distributional assumption for the random effects. (Verbeke and Molenberghs, 2000). Thus, Verbeke (1995) and Verbeke and Lesaffre (1996a), proposed to extend the Linear Mixed Model by allowing the random effects to be sampled from a mixture of g normal distributions with equal covariance, while Magder and Zeger (1996) proposed extending the Linear Mixed Model though treating the g components as an unknown parameter, to be estimated form the data. These are computational intensive models that will not be done in this study but we shall assume that normality assumption for the random effects holds. However, box plots of the random effects are plotted to show that they have mean zero and constant variance.

3.6 Generalized Estimating Equations

The main issue with full likelihood approaches for marginal models is the computational complexity they entail. The net benefit can be efficiency gain, but this comes at the cost of an increased risk of model misspecification. Other models may become unwieldy in computational terms when the number of repeated measures increases beyond a moderate number. (Molenberghs and Verbeke, 2005). For these reasons, when we are mainly interested in first order marginal mean parameters and pairwise interactions, a full likelihood procedure can be replaced by quasi-likelihood based methods (McCullagh and Nelder, 1989).

The generalized estimating equations (GEEs) (Liang and Zeger, 1986) are marginal models that can be used to study the association for the non-Gaussian data. These GEEs require the correct specification of the univariate marginal distribution and they introduce a working correlation structure in the marginal covariance matrix. The GEE models are a direct extension of basic quasi-likelihood theory from cross-sectional to repeated or correlated measurements. GEE yields consistent estimators even when the association structure is misspecified; this is due to the robustness property they have. However, severe misspecification may affect the efficiency of the GEE estimators. Although GEEs are robust, they are less adequate when some scientific interest is on the association parameters (Molenberghs and Verbeke, 2005).

It is important to note that these GEEs are only valid under a strong assumption that the data is MCAR if missingness exists. In case the data is MAR, an extension of the GEEs is used; Weighted GEEs (WGEEs). The general idea of the WGEEs is to weight each subject's measurements in the GEEs by the inverse probability that a subject drops out at that particular measurement occasion (Robins *et al.*, 1995). In this case, a macro (available at http://www.ibiostat.be/software/Longitudinal.asp) is applied which weights each respondent's measurements by the inverse probability that that particular measurement is missing.

4 Results

4.1 Hospital Characteristics

In this study only the 90 acute hospitals are considered. They were predominantly Dutch speaking (58) while 31 were French speaking and only 1 was both Dutch and French speaking.

4.2 Respondent Characteristics

Respondents' characteristics are set out in Table 2, based on the respondents' answers to survey questions about their hospital work area, staff position, direct interaction with patients, professional experience, working time in the hospital, how long they have worked in the current work area, how long they have worked in the current hospital, overall patient safety grade and number of events reported in the past 12 months. In total, there were 47,635 respondents (overall response rate=51.9%), including 28,385 nurses, head nurses and nursing aids, 4656 physicians and physician assistants, 2697 therapists, and 757 pharmacists and pharmacy assistants. It can be seen that most respondents did not indicate their unit (18.4%) while for those that indicated, most worked in Internal medicine (10.9%) followed by surgery (10.3%) and the least came from Pharmacy (1.7%). Respondents were predominantly nurses (48.1%) followed by Nurse Assistants (7.2%). 10% did not indicate their profession. Almost 30% of the respondents had worked within their hospital for 21 years or more and 28% had worked in their current unit for 1-5 years. Similarly, about 30% of the respondents have 21 years or more of professional experience, 60% work for 20-39 hours per week and 50% view the overall patient safety grade as "acceptable". It's also worth noting that most of the respondents (about 85%) had direct patient interaction and almost 40% had never reported any event in the past 12 months. The response variable, "Overall perceptions of patient safety (o1score)" has an average of 3.246 with a minimum of 1 and a maximum of 5.

Overall, 58.5% of the respondents were consistent with a positive overall perception of patient safety culture.

Table 2: Respondent characteristics

Characteristics	Number (%)	Characteristics	Number (%)
Total no. of respondents	47635 (100%)	**Professional experience (H6)**	**44758 (94%)**
Work area/ Unit (A0)	**38852 (81.6%)**	Less than 1 year	1902 (4.0%)
Many different units	3147 (6.6%)	1 to 5 years	8423 (17.7%)
Internal Medicine	5201 (10.9%)	6 to 10 years	8035 (16.9 %)
Surgery	4923 (10.3%)	11 to 15 years	5880 (12.3%)
Operating theatre	2588 (5.4%)	16 to 20 years	6582 (13.8%)
Gynecology/ obstetrics	1918 (4%)	21 years or more	13936 (29.3%)
Pediatrics	1653 (3.5%)	Not specified	2877 (6%)
Intensive care unit	2349 (4.9%)	**Working time in hospital (H3)**	**45030 (94.5%)**
Emergency	1701 (3.6%)	Less than 20 hours per week	4885 (10.3%)
Revalidation	1710 (3.6%)	20 to 39 hours per week	28532 (59.5%)
Geriatrics	2563 (5.4%)	40 to 59 hours per week	9638 (20.2%)
Psychiatry	1367 (2.9%)	60 to 79 hours per week	1553 (3.3%)
Diagnostics	4680 (9.8%)	80 hours per week or more	422 (0.9%)
Pharmacy	824 (1.7%)	Not specified	2605 (5.5%)
Other	4228 (8.9%)	**Period in current unit (H2)**	**45240 (95.0%)**
Not specified	8783 (18.4%)	Less than 1 year	4450 (9.3%)
Profession (H4)	**42851 (90%)**	1 to 5 years	13440 (28.2%)
Nurse	22910 (48.1%)	6 to 10 years	9588 (20.1 %)
Head nurse	2038 (4.3%)	11 to 15 years	5476 (11.5%)
Nurse assistant	3437 (7.2%)	16 to 20 years	5102 (10.7%)
Physician	3222 (6.8%)	21 years or more	7184 (15.1%)
Head Physician	1153 (2.4%)	Not specified	2877 (6.0%)
Physician assistant	281 (0.6%)	**Period in current hospital (H1)**	**45292 (95.1%)**
Pharmacist	304 (0.6%)	Less than 1 year	2704 (5.7%)
Pharmacist assistant	453 (1.0%)	1 to 5 years	9453 (19.8%)
Middle management	1517 (3.2%)	6 to 10 years	7973 (16.7 %)
Technician	2063 (4.3%)	11 to 15 years	5426 (11.4%)
Therapist	2697 (5.7%)	16 to 20 years	6500 (13.6%)
Other	2776 (5.8%)	21 years or more	13236 (27.8%)
Not specified	4784 (10%)	Not specified	2343 (4.9%)
Interaction with patients (H5)	**44669 (93.8%)**	**Events reported in 12 mts (G1)**	**45154 (94.8%)**
YES	40247 (84.5%)	No event reported	18865 (39.6%)
NO	4422 (9.3%)	1-2 events reported	14301 (30.0%)
Not specified	2966 (6.2%)	3-5 events reported	7353 (15.4%)
		6-10 events reported	2620 (5.5%)
		11-20 events reported	1062 (2.2%)
		21 or more events reported	953 (2.0%)
		Not specified	2481(5.2%)

4.3 Differences in PPR and average scores among Professions

From Figure 1, we find the highest PPR among the head physician implying that they could have the highest positive perception of patient safety and the lowest among the Middle management. Comparing the professions of interest, ie Physicians, Nurses and Pharmacists, the Physician shows the highest positive patient safety perception and the lowest is shown by the Nurse.

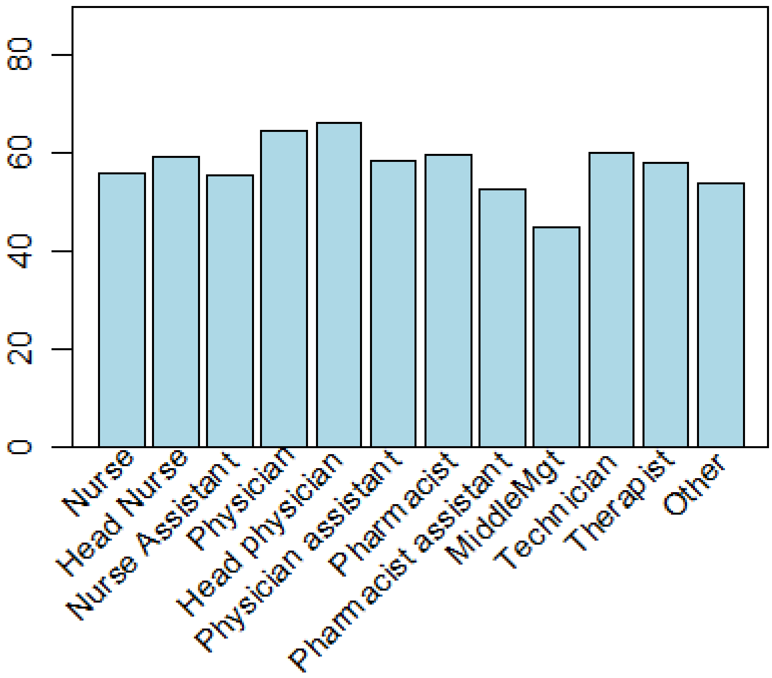

Figure 1: Percentage Positive Responses by Profession

Figure 2 shows the mean scores among professions between hospitals. The technician shows the highest average score and with the least variability between the hospitals and the lowest among the middle management and with a considerable variability between hospitals. Comparing the Professions of interest ie the Nurses, Physicians and Pharmacists, the Pharmacists show the highest average score followed by the physicians. Much more variability is seen with the pharmacist than the nurses and physicians between hospitals. The nurses show least variability in their scores between hospitals than the physicians and pharmacists.

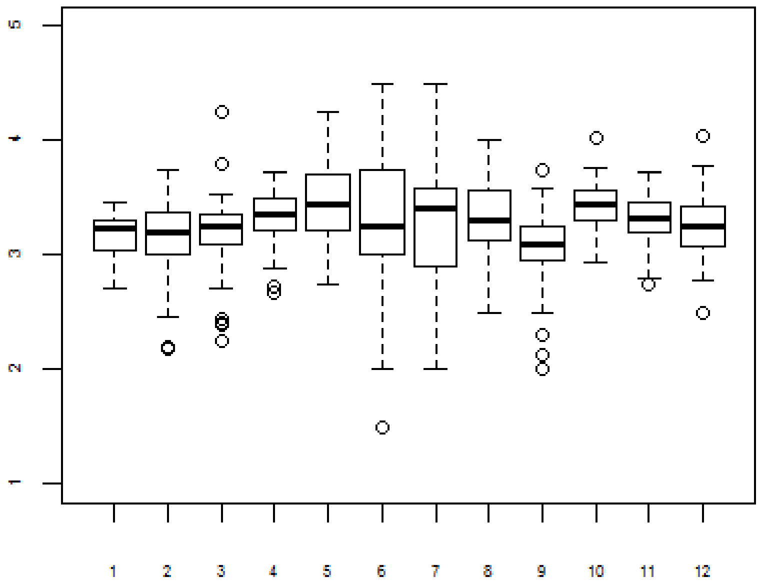

Figure2: Differences in Average scores among Professions (1=Nurse, 2=Assistant Nurse, 3=Head Nurse, 4=Physician, 5=Assistant Physician, 6=Head Physician, 7=Pharmacist, 8=Assistant Pharmacist, 9=Middle Management, 10=Technician, 11=Therapist, 12=Other)

4.4 Differences in PPR and average scores among Work Units

Comparing all the units, the diagnostics unit shows the highest positive perception towards patient safety and the lowest is shown by the Emergency department. In this study, Work units considered to be intrinsically hazardous are Operating Theatre (OT) and Emergency Department (ED) and Intensive Care Unit (ICU). From Figure 3, comparing them shows that the ICU has the highest positive perception towards patient safety though not much higher than the OT and the lowest is from the ED. Among the units considered to be of low intrinsic hazard, ie the Pediatrics, Psychiatry and revalidation, we don't see much difference in their positive perception towards patient safety though the revalidation has the highest and the lowest is shown by Psychiatry.

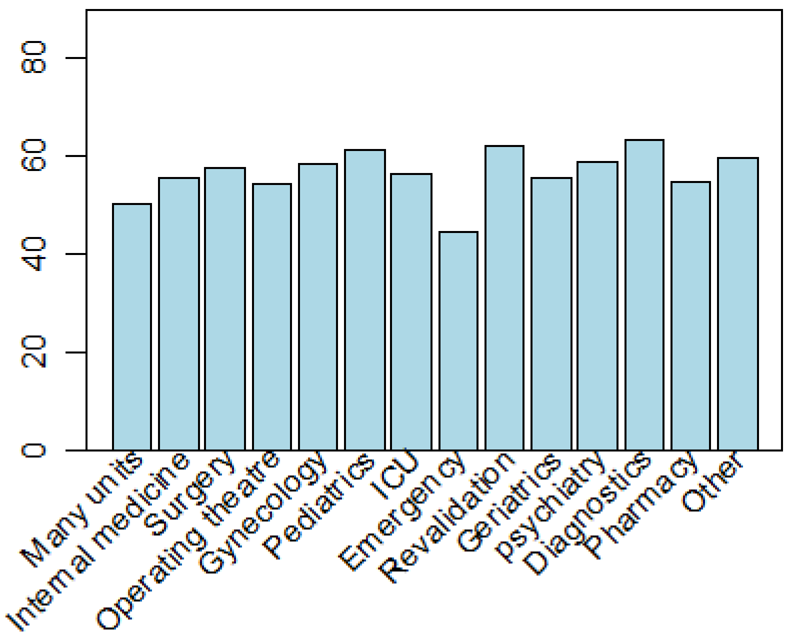

Figure 3: Percent Positive Responses by Work Units

Figure 4 shows the mean scores among work units between hospitals. It can be seen that the diagnostics unit has the highest average score and also the least variability in scores between hospitals. And the Emergency unit has the lowest average score but with some considerable variation between hospitals. Among the intrinsically hazardous units, the ICU performs best and the ED performs worst. There is some variation between hospitals in each work unit with psychiatry seeming to have the highest variation in its average scores between the hospitals.

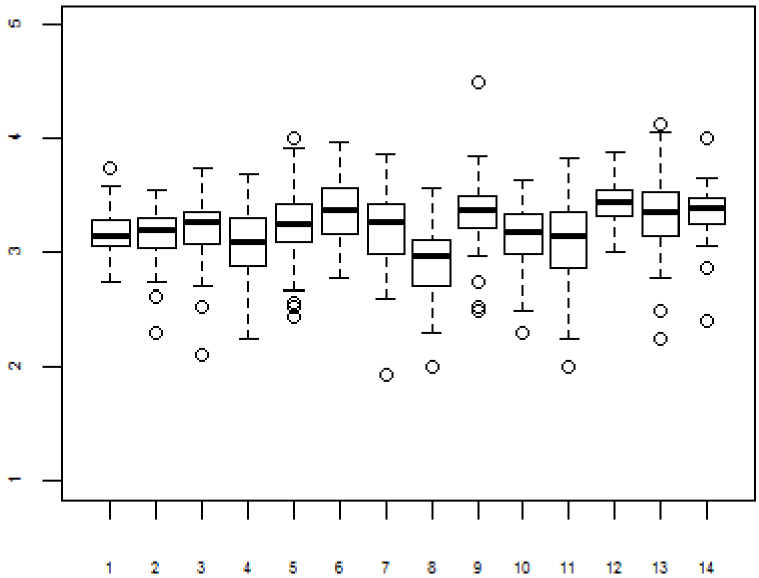

Figure 4: Differences in Average scores among Units (1=Many Units, 2=Internal Medicine, 3=Surgery, 4=Theatre, 5=Gynecology, 6=Pediatrics, 7=ICU, 8=Emergency, 9=Revalidation,10=Geriatrics,11=Psychiatry, 12=Diagnostics, 13=Pharmacy, 14=Other)

4.5 Differences in PPR and average scores Among hospitals

Figure 5 shows the differences in PPR among hospitals. It can be seen there is a substantial difference in the PPR among the hospitals with the dutch-speaking hospitals showing the highest positive perception towards patient safety, followed by the French speaking hospitals and the hospitals that speak both French and Dutch have the lowest positive perception towards patient safety.

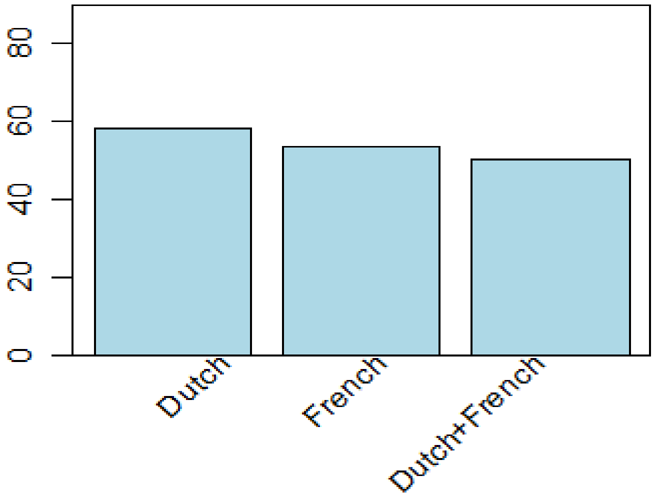

Figure 5. Percentage Positive Responses among hospitals

4.6 Exploring missingness

To provide insight into which factors influence missingness, a logistic regression model was built for the missingness indicator, in terms of the other covariates. Table 3 shows that some covariates in the model are significant. The probability of missingness depends on whether the respond is in direct contact with patients or not, how long the respondent has worked in their current profession and the hospital language. The parameter estimates from the logistic regression model (not shown) indicate that those with direct contact with patients have a higher probability of missingness than those with no direct contact. Respondents who have worked for a longer period in their current profession are more likely to have missingness than those who have worked for a shorter time. With the hospital language, those that speak both Dutch and French are most likely to have missingness than those that speak Dutch or French. The fact that the missingness depends on other variables implies that there is evidence against MCAR in favor of MAR.

Table 3. ***Analysis of effects for a logistic regression model to describe missingness***

Effect	DF	Wald Chi-Square	Pr > ChiSq
a0	13	2.8687	0.9984
h1	1	0.0335	0.8548
h2	1	1.6319	0.2014
h3	1	1.8734	0.1711
h4	11	9.3165	0.5927
h5	1	11.5798	0.0007
h6	1	6.7087	0.0096
g1	1	2.0147	0.1558
Ttaal	2	12.8609	0.0016

Table 4 presents a part the 175 missing patterns with the number and percentage of respondents having the corresponding pattern. One can observe that a substantial portion of the data is subject to missingness. Of the 47635 respondents that completed the questionnaires, 34938 respondents (73.35%) have all questions answered where as the remaining 12697 (26.65%) don't have complete records.

The methods used to take this missingness into account valid under the MAR assumption are; using the direct likelihood approach and Multiple Imputation for the continuous outcome, in addition to Weighted GEE for the binary outcome as described in (3.3), (3.4) and (3.6)

After studying the missing patterns as shown in Table 4 which is non-monotone, enough data is imputed to make a monotone missingness as shown in Table 5 and then the appropriate analysis methods applied.

Table 4: Part of the missing patterns and the frequencies with which they occur

HOSPCODE	Taal	YEAR	A0	H1	H2	H3	H4	H5	H6	G1	O1SCORE	Freq	Percent
X	X	X	X	X	X	X	X	X	X	X	X	34938	73.35
X	X	X	.	X	X	X	X	X	X	X	X	4236	8.89
X	X	X	.	X	X	X	.	X	X	X	X	1973	4.14
X	X	X	.	.	.	.	.	.	.	X	X	1659	3.48
X	X	X	X	X	X	X	X	X	X	.	X	1545	3.24
X	X	X	X	X	X	X	X	.	.	X	X	405	0.85
X	X	X	X	X	X	X	.	X	X	X	X	308	0.65
X	X	X	X	X	X	.	X	X	X	X	X	249	0.52
X	X	X	X	X	X	X	X	.	X	X	X	222	0.47
X	X	X	.	X	X	X	X	X	X	.	X	198	0.42
X	X	X	X	X	X	X	X	X	.	X	X	123	0.26
X	X	X	X	.	.	.	.	.	.	.	X	113	0.24
X	X	X	X	X	.	X	X	X	X	X	X	110	0.23
X	X	X	.	X	X	X	.	X	X	.	X	106	0.22
X	X	X	X	.	X	X	X	X	X	X	X	101	0.21
X	X	X	.	X	X	X	X	.	X	X	X	95	0.2
X	X	X	X	.	.	.	.	X	X	.	X	78	0.16
X	X	X	.	X	X	X	X	.	.	X	X	71	0.15
X	X	X	.	.	.	.	.	.	.	.	X	66	0.14
X	X	X	X	X	X	X	X	X	X	X	.	50	0.1
X	X	X	X	X	X	X	.	X	X	.	X	46	0.1
X	X	X	.	X	X	.	X	X	X	X	X	46	0.1
X	X	X	.	X	X	.	.	X	X	X	X	45	0.09
X	X	X	.	X	X	X	.	.	.	X	X	44	0.09
X	X	X	X	X	X	X	.	.	.	X	X	43	0.09
X	X	X	X	.	.	.	.	.	.	X	X	38	0.08
X	X	X	X	.	.	.	X	X	.	X	X	36	0.08
X	X	X	X	X	X	X	X	.	X	.	X	35	0.07
X	X	X	X	X	X	.	X	X	X	.	X	34	0.07
X	X	X	X	X	X	X	X	.	.	.	X	24	0.05
X	X	X	X	X	X	.	.	X	X	X	X	20	0.04
X	X	X	X	.	X	X	X	X	X	.	X	19	0.04
X	X	X	X	.	.	X	X	X	.	X	X	19	0.04
X	X	X	X	X	.	X	X	X	X	.	X	18	0.04
X	X	X	.	X	X	X	X	X	X	X	.	18	0.04
X	X	X	.	X	.	X	X	X	X	X	X	18	0.04
X	X	X	X	X	X	X	.	.	X	X	X	17	0.04
X	X	X	.	X	X	X	.	.	X	X	X	17	0.04
X	X	X	X	.	.	.	.	X	.	X	X	16	0.03
X	X	X	.	X	X	X	X	X	.	X	X	16	0.03
X	X	X	X	.	.	.	X	X	X	.	X	15	0.03
X	X	X	X	X	X	X	X	X	.	.	X	13	0.03
X	X	X	X	X	X	X	X	X	X	.	.	12	0.03
X	X	X	X	.	.	X	X	X	X	X	X	12	0.03
X	X	X	.	.	.	.	.	X	X	.	X	12	0.03
X	X	X	X	X	X	.	X	X	.	X	X	10	0.02
X	X	X	X	X	X	.	X	.	X	X	X	10	0.02
X	X	X	X	.	.	.	X	.	.	.	X	10	0.02
X	X	X	.	X	X	X	.	X	.	X	X	10	0.02
X	X	X	.	.	X	X	X	X	X	X	X	10	0.02
X	X	X	X	X	X	X	.	X	.	X	X	8	0.02

Table 5: Monotone Missing Patterns

HOSPCODE	Taal	YEAR	A0	H1	H2	H3	H4	H5	H6	G1	O1SCORE	Freq	Percent
X	X	X	X	X	X	X	X	X	X	X	X	142611	99.79
X	X	X	X	X	X	X	X	X	X	X	.	243	0.17
X	X	X	X	X	X	X	X	X	X	.	.	45	0.03
X	X	X	X	X	X	X	X	X	.	.	.	3	0
X	X	X	.	.	.	.	.	.	.	.	.	3	0

4.7 The Linear Mixed Model

A Linear Mixed Model (LMM) was fitted to the data to examine the relationship of work unit, profession and all respondent characteristics with the outcome dimension (Overall perceptions of patient safety). To account for the correlation between respondents from the same hospital and work unit, which were significant, hospital and work unit were included as random effects in the form of a 2-level random effects analysis and they were significant. However the work unit was also included as a fixed effect since we are interested in seeing its effect on the safety culture perceptions. According to Rogers *et al.* (2004), risks of making an error increase when work shifts are longer than twelve hours, when nurses worked overtime, or when they worked more than forty hours per week and more so with staff that have worked in a unit for long periods of time. Therefore, interactions between Profession and how long one has worked in the current unit and also between Profession and hours worked per week were considered. However only the interaction between profession and how long one has worked in the current unit turned out significant and therefore are included in the model.

The model was fitted separately considering the missingness in two different ways; fitting the model to the Multiple imputed data and secondly, using the direct (observed data) likelihood approach. As shown in Table 6, the results from the two analysis approaches show similar parameter estimates.

More so from Table 6, it can be seen that the respondents in most of the units have a better safety perception than those who worked in the internal medicine. The respondents in the diagnostics unit have the best patient safety perception while the emergency unit has the lowest. With Profession, we cannot compare among the different professions since their effect depends on how long they have worked in the current unit. From the significant interactions, it can be seen that the perception of the Head Nurse, Physician, Head Physician, Assistant Physician and Therapist also depends on how long they have worked in the current work unit with the Assistant physician as best followed by Head Nurse, Head Physician, Therapist and finally the physician. More so, it can be seen that the respondents that had worked for a shorter time in the current hospital showed a better safety perception than those who worked longer. In addition, those that worked for fewer hours and with fewer events reported had a better perception and also the Dutch speaking hospitals were the best followed by the French and those that spoke both Dutch and French. The factors which are significant are Work unit, how long one has worked in current hospital, interaction between Profession and how long one has worked in the current unit, Number of hours worked per week, Number of events reported in the past 12 months and Language used in the hospital. These can be taken as the factors influencing differences in patient safety culture. The variance parameter estimates show little variability between hospitals (0.005), a little more variability within hospitals and between work units (0.022) but much more variability within work units (0.398) and they are all significant.

Table 6: Linear Mixed Model parameter estimates from the different approaches

	Multiple Imputation		Direct Likelihood	
Parameter	**Estimate(s.e)**	**p-value**	**Estimate(s.e)**	**p-value**
Intercept	3.330(0.018)	<.0001	3.56(0.029)	<.0001
Work Area, A0 (Reference=Internal Medicine)				
Many Units	-0.101(0.017)	<.0001	-0.047(0.031)	0.0283
Surgery	0.013(0.022)	0.5724	0.039(0.029)	0.1759
Operating theatre	-0.162(0.039)	<.0001	-0.113(0.031)	0.0003
Gynecology	0.03(0.04)	0.4431	0.033(0.032)	0.3104
Pediatrics	0.067(0.03)	0.0232	0.149(0.033)	<.0001
Intensive Care Unit	0.04(0.041)	0.341	0.049(0.031)	0.1204
Emergency	-0.323(0.028)	<.0001	-0.254(0.032)	<.0001
Revalidation	0.078(0.024)	0.0013	0.142(0.034)	<.0001
Geriatrics	-0.055(0.023)	0.1059	-0.008(0.031)	0.8076
Psychiatry	0.004(0.042)	0.9211	0.021(0.037)	0.5763
MIS(Diagnostics)	0.161(0.019)	<.0001	0.237(0.03)	<.0001
Pharmacy	-0.011(0.049)	0.8207	-0.006(0.064)	0.9232
Other	0.121(0.019)	<.0001	0.193(0.031)	<.0001
Profession, H4 (Reference=Nurse)				
Head Nurse	-0.096(0.035)	0.0961	-0.076(0.038)	0.0479
Assistant Nurse	0.036(0.024)	0.1311	0.045(0.029)	0.1235
Physician	0.171(0.031)	<.0001	0.177(0.033)	<.0001
Head Physician	0.024(0.058)	0.6748	0.054(0.065)	0.4075
Assistant Physician	-0.07(0.069)	0.305	-0.047(0.074)	0.5301
Pharmacist	0.147(0.094)	0.1167	0.191(0.101)	0.058
Assistant Pharmacist	0.055(0.09)	0.5391	0.129(0.093)	0.1664
Middle Management	-0.009(0.037)	0.8036	-0.007(0.049)	0.88
Technician	-0.015(0.037)	0.6816	-0.006(0.042)	0.8843
Therapist	0.045(0.029)	0.1244	0.013(0.033)	0.7011
Other	-0.035(0.024)	0.1388	-0.019(0.033)	0.5784
Period worked in this hospital, **H1**	-0.018(0.003)	<.0001	-0.017(0.003)	<.0001
Period worked in work unit, **H2**	-0.011(0.003)	0.001	-0.017(0.004)	<.0001
Hours worked per week, **H3**	-0.029(0.004)	<.0001	-0.032(0.005)	<.0001
Number of events reported, **G1**	-0.068(0.003)	<.0001	-0.071(0.003)	<.0001

Head Nurse*H2	0.045(0.009)	<.0001	0.047(0.01)	<.0001
Assistant Nurse*H2	-0.0004(0.006)	0.9549	-0.002(0.008)	0.8452
Physician*H2	0.014(0.008)	0.0372	0.023(0.008)	0.0062
Head Physician*H2	0.068(0.013)	<.0001	0.072(0.014)	<.0001
Assistant Physician*H2	0.074(0.035)	0.0378	0.109(0.031)	0.0005
Pharmacist*H2	0.006(0.025)	0.7942	0.016(0.024)	0.5098
Assistant Pharmacist*H2	0.015(0.015)	0.3035	0.025(0.022)	0.2536
Middle Management*H2	0.01(0.01)	0.2839	0.007(0.014)	0.6038
Technician*H2	0.023(0.009)	0.0077	0.02(0.01)	0.0344
Therapist*H2	0.022(0.008)	0.0035	0.026(0.009)	0.0028
Other*H2	0.021(0.007)	0.0014	0.019(0.009)	0.0473
Language, taal (Reference=Dutch)				
Both French and Dutch	-0.267(0.013)	<.0001	-0.432(0.094)	<.0001
French	-0.188(0.086)	0.0285	-0.278(0.023)	<.0001

4.8 Generalized Estimating Equations (GEE) for the binary outcome

A GEE Model was fitted to the data to examine the relationship of work unit, profession and all respondent characteristics with the probability of having a positive perception towards patient safety. The same interactions as explained in section 4.7 were considered but none of them was significant and therefore are not included in the model.

The model was fitted separately considering the missingness in two different ways; fitting the model to the Multiple imputed data and secondly, using the weighted GEE. As shown in Table 7, the results from the two analysis approaches show similar parameter estimates and standard errors.

Considering work unit, it can be seen that most of the units have a higher probability of a positive safety perception than the internal medicine apart from the many units, operating theatre and emergency. The highest probability of a positive safety culture perception is shown in the diagnostics unit and the lowest is in the emergency unit. With Profession, we see that most of the professions have a higher probability of a positive perception than the nurse. The highest probability is shown by the head physician followed by the physician, assistant physician, pharmacist, Technician and finally the Head Nurse. More so, it can be seen that the respondents that had worked for a shorter time in the current hospital, shorter time in the current profession showed a higher probability of a positive safety perception than those who worked longer. In addition, those that worked for fewer hours and with fewer events reported had a higher probability of a positive perception and also the probability of the Dutch speaking hospitals was highest followed by the French and finally those that spoke both Dutch and French. The factors which are significant are Work unit, Profession, how long one has worked in current hospital, how long one has worked in the profession, Number of hours worked per week, Number of events reported in the past 12 months and Language used in the hospital. These can be taken as the factors influencing the probability of having a positive overall perception towards patient safety culture.

Table 7. GEE Parameter estimates (empirically corrected se) for the different approaches

	Multiple Imputation+GEE		Weighted GEE	
Parameter	**Estimate(s.e)**	**p-value**	**Estimate(s.e)**	**p-value**
Intercept	1.667(0.058)	<.0001	1.642(0.057)	<.0001
Work Area, A0 (Reference=Internal Medicine)				
Many Units	-0.329(0.032)	<.0001	-0.322(0.031)	<.0001
Surgery	0.019(0.016)	0.0321	0.036(0.011)	0.0007
Operating theatre	-0.382(0.018)	<.0001	-0.412(0.015)	<.0001
Gynecology	0.056(0.015)	0.0001	0.044(0.014)	0.0013
Pediatrics	0.177(0.023)	<.0001	0.168(0.024)	<.0001
Intensive Care Unit	0.084(0.017)	<.0001	0.081(0.011)	<.0001
Emergency	-0.799(0.016)	<.0001	-0.805(0.011)	<.0001
Revalidation	0.248(0.02)	<.0001	0.234(0.019)	<.0001
Geriatrics	0.143(0.023)	0.5401	0.176(0.018)	<.0001
Psychiatry	0.072(0.013)	<.0001	0.109(0.01)	<.0001
MIS(Diagnostics)	0.383(0.015)	<.0001	0.366(0.013)	<.0001
Pharmacy	0.044(0.073)	<.0001	0.071(0.077)	0.3524
Other	0.35(0.017)	<.0001	0.326(0.018)	<.0001
Profession, H4 (Reference=Nurse)				
Head Nurse	0.124(0.036)	0.0007	0.116(0.038)	0.0022
Assistant Nurse	0.082(0.058)	0.1576	0.081(0.059)	0.1692
Physician	0.562(0.094)	<.0001	0.562(0.092)	<.0001
Head Physician	0.761(0.099)	<.0001	0.756(0.095)	<.0001
Assistant Physician	0.256(0.144)	0.0059	0.249(0.142)	0.0802
Pharmacist	0.365(0.142)	0.0104	0.324(0.146)	0.0266
Assistant Pharmacist	0.051(0.097)	0.6008	0.006(0.096)	0.9472
Middle Management	-0.089(0.118)	0.4529	-0.083(0.117)	0.4826
Technician	0.218(0.043)	<.0001	0.211(0.042)	<.0001
Therapist	0.256(0.086)	0.0628	0.261(0.084)	0.1019
Other	0.024(0.073)	0.7399	-0.025(0.075)	0.7371
Period worked in this hospital, **H1**	-0.034(0.014)	0.0135	-0.029(0.01)	0.0026
Hours worked per week, **H3**	-0.101(0.015)	<.0001	-0.097(0.015)	<.0001
Period worked in this profession, **H6**	-0.039(0.012)	0.0008	-0.036(0.011)	0.001
Number of events reported, **G1**	-0.163(0.016)	<.0001	-0.159(0.015)	<.0001
Language, taal (Reference=Dutch)				
Both French and Dutch	-0.659(0.056)	<.0001	-0.666(0.053)	<.0001
French	-0.431(0.215)	0.0444	-0.405(0.21)	0.0542

5 Diagnostics

Figure 6 shows box plots of the studentized residuals for each of the hospitals. From the figure, it appears that the residuals are centered at zero with approximately constant variance.

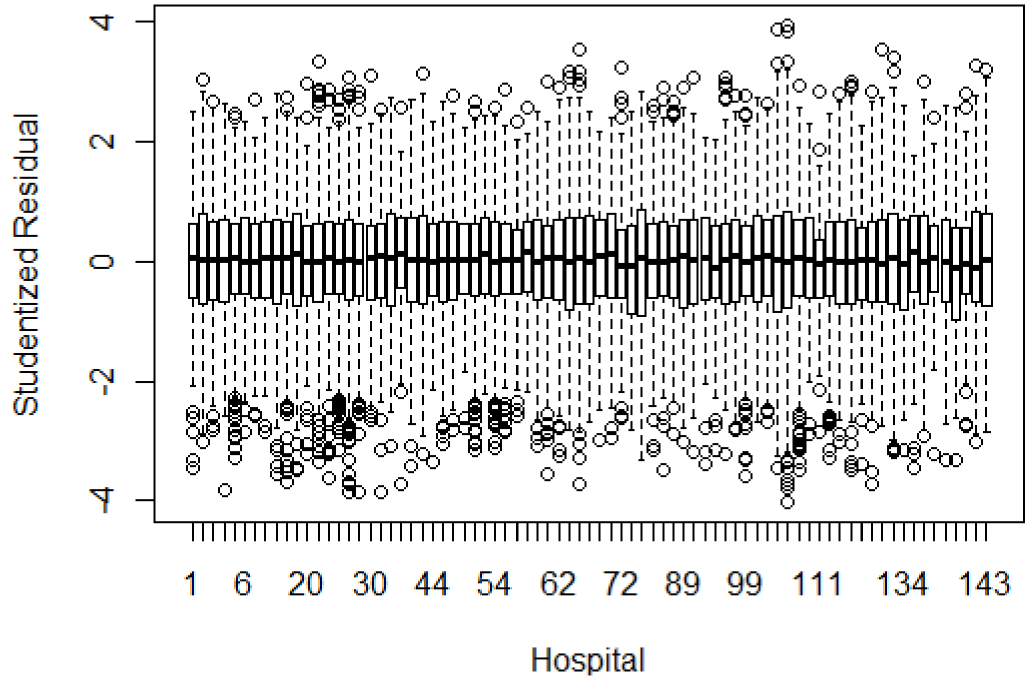

Figure 6. Box plots of studentized residuals

For normality, Figure 7 shows the normal Q-Q plot of the residuals. This plot doesn't indicate any obvious violation of the normality assumption of the errors.

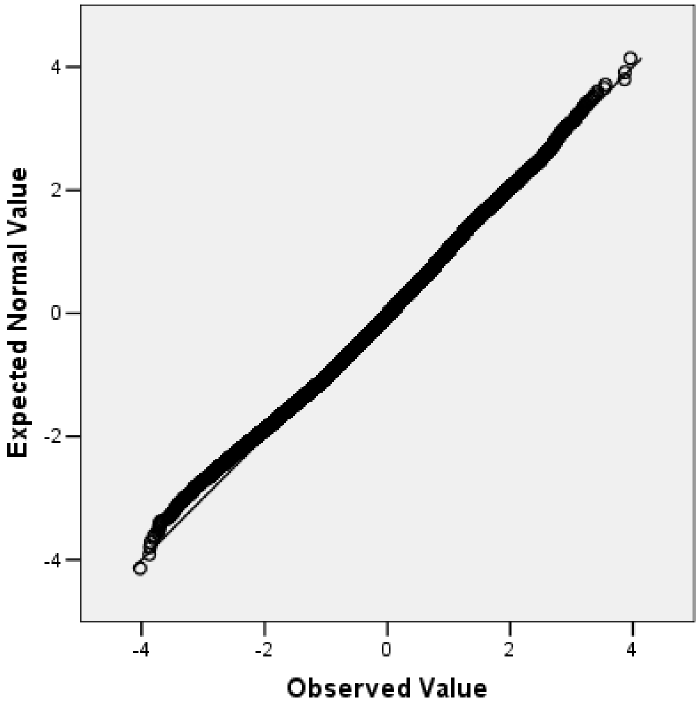

Figure 7. Normal Q-Q plot of studentized residuals

Likewise for the random effects, Figure 8 shows the box plots of the random effects for each of the hospitals. From the figure, it appears that the random effects are infact centered at zero with approximately constant variance.

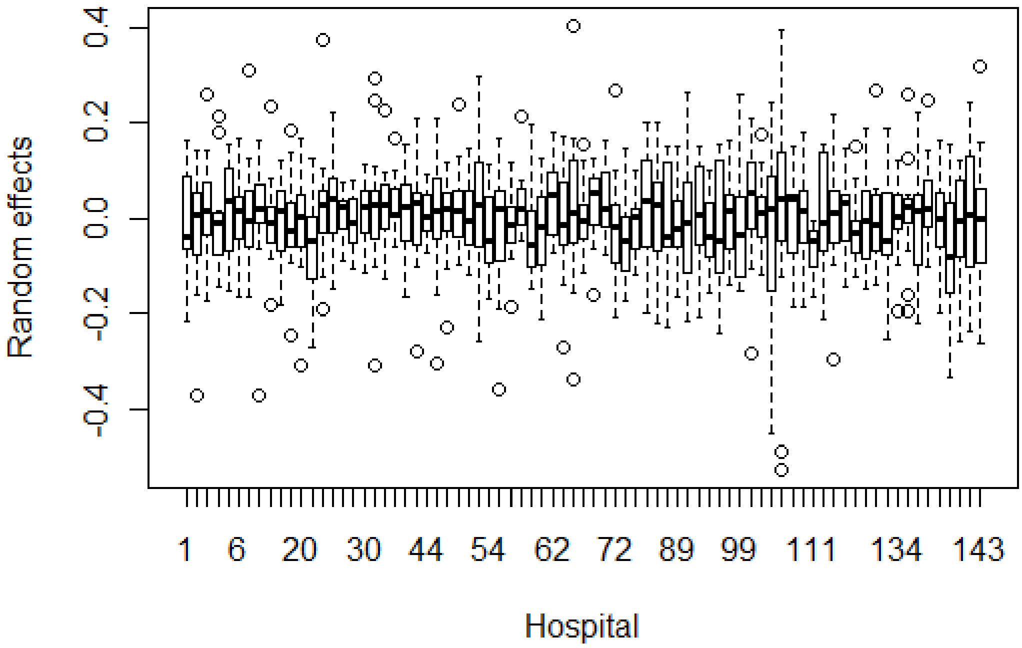

Figure 8. Box plots of random effects

6 Discussion

Patient safety culture in 90 acute Belgian hospitals was measured with the main objective to explore ways in which safety culture varies among these hospitals and by characteristics of hospital workers, their work areas and their professions. Examined were results from a survey that measured healthcare workers' perceptions of safety culture by using the "Overall perceptions of patient safety" as the outcome score. Particularly, the key questions were to assess (1) whether there is a significant variation in safety culture based on professional background and working units in the hospital, (2) variation in patient safety culture within and across hospitals and (3) whether there are other factors, that is, hospital (eg language spoken) and individual characteristics (eg experience, working hours) that may influence the patient safety culture.

Overall, 58.5% of the respondents were consistent with a positive overall perception of patient safety culture. Results from the Linear Mixed Model highlight differences in attitudes and perceptions among work units and professions. One key finding was that the units considered to be of greater intrinsic Hazard , particularly the Emergency unit and Operating Theatre perceived the lowest levels of safety culture while the units of less intrinsic Hazard, eg the Diagnostics and Paediatrics perceived the highest levels of safety culture. This could suggest that the higher level of risk and complexity and faster pace associated with work performed in the Emergency unit continue to require relatively more attention than other areas.

The second key finding was that the longer one worked in a particular hospital or a particular unit, the worse was their perception of patient safety. This is could be due to the fact that workers who have stayed in the same hospital or work unit for long tend to relax which reduces their sensitivity to the issues of patient safety.

Moreso, the less the number of events reported the better the overall perception of patient safety. This implies that the more one becomes more sensitive to patient safety, the less they are likely to make mistakes and vice versa.

Furthermore, the number of hours worked per week had an effect on the patient safety perception in such a way that respondents that worked shorter hours per week showed better perceptions than those who worked longer hours. This is expected since the workers who work longer hours get very tired and thus become less sensitive to patient's safety. It was also discovered that the effect of the respondent's profession depends on how long they have worked in that particular work unit.

From the GEE model which models the probability to have a positive overall perception of patient safety, similar conclusions can be made like in the LMM model except that the interaction between the profession and period worked in a particular unit is not significant. This allows us to compare the probabilities of a positive perception among the professions. Generally, all professions show a better perception than the nurses. Comparing the professions of interest shows that the physician performs best followed by the Pharmacist and lastly the Nurse. This could imply that status and authority differences between physicians and nurses may cause different psychological barriers to better safety culture. High status and expectations associated with their role may cause physicians to have more feelings of individual responsibility for patients' well being than the nurses.

There are some limitations to this study. First, the hospitals were not randomly selected. The database only included data of hospitals that voluntarily submitted their data for comparison and did not represent a randomly selected sample of all Belgian acute hospitals but only 79.6% of them. Secondly, hospitals used different survey methods (paper, electronic or mixed mode) and not all of the hospitals sent reminders, which could have led to differences in response rates.

7 Conclusion

The results highlight differences in perceptions among and within work units and professions. The individual characteristics that that influence differences in patient safety culture are (1) How long one has worked in that particular hospital, (2) How long one has worked in the current work unit, (3) How many hours are worked per week, (4), One's profession, (5), How long one has worked in the current profession, (6) How many events one has reported in the past 12 months, and (7) The work unit that one works in. The hospital characteristic that influences differences in patient safety culture is the language used in the hospital.

Findings suggest that safety culture improvement efforts might involve greater attention to the work units considered of greater intrinsic hazard, particularly the Emergency unit and Operating theatre. Reasonable strategies for improving safety culture and achieving highly reliable patient safety should also be tailored for Nurses. To address this, it may require that hospitals augment their efforts to reward, promote, evaluate, and train for safety, particularly relative to other metric of performance. The small variability between hospitals suggests that directing interventions at the hospital level is not a good idea; unit level improvement efforts seem more worthwhile.

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Appendix

SAS codes used in the analysis

Linear Mixed Model

```
/***Direct likelihood***/
PROC MIXED DATA = thesiscat covtest;
CLASS TA0 HOSPcode TH4 Ttaal ;
MODEL o1score = TA0 H1 H2 H3 TH4 G1 Ttaal TH4*H2/ S;
RANDOM INTERCEPT /SUB=HOSPcode type=un;
RANDOM INTERCEPT/SUB=A0(HOSPcode) type=un;
RUN;

/***LMM+MI***/
/*first step imputation to produce monotone missingness*/
proc MI data=thesis nimpute=5 seed=33 out=outimputed;
var A0 H4 Ttaal hospcode H1 H2 H3 G1 o1score;
mcmc impute=monotone;
run;
quit;

/*first step imputation to produce monotone missingness*/
proc MI  nimpute=5 data=outimputed out=outimpute2 seed=333;
class A0 H4 Ttaal hospcode;
var A0 H4 Ttaal hospcode H1 H2 H3 G1 o1score;
monotone regression (H1=A0 H4 Ttaal hospcode);
monotone regression (H2=A0 H4 Ttaal hospcode H1);
monotone regression (H3=A0 H4 Ttaal hospcode H1 H2);
monotone regression (G1=A0 H4 Ttaal hospcode H1 H2 H3);
monotone regression (o1score=A0 H4 Ttaal hospcode H1 H2 H3 G1);
run;

proc mixed data=outimpute2 covtest;
class hospcode;
model o1score= A0a A0c A0d A0e A0f A0g A0h A0i A0j A0k A0l A0m A0n H1 H3
H4b H4c H4d H4e H4f H4g H4h H4i H4j H4k H4l H4b*H2 H4c*H2 H4d*H2 H4e*H2
H4f*H2 H4g*H2 H4h*H2 H4i*H2 H4j*H2 H4k*H2 H4l*H2 G1 Ttaalb Ttaalc /
solution;
RANDOM INTERCEPT /SUB=HOSPcode type=un;
RANDOM INTERCEPT/SUB=A0(HOSPcode) type=un;
by _imputation_;
ods output SolutionF=result;
RUN;
PROC MIANALYZE parms = result;
modeleffects intercept A0a A0c A0d A0e A0f A0g A0h A0i A0j A0k A0l A0m A0n
H1 H2 H3 H4b H4c H4d H4e H4f H4g H4h H4i H4j H4k H4l H4b*H2 H4c*H2 H4d*H2
H4e*H2 H4f*H2 H4g*H2 H4h*H2 H4i*H2 H4j*H2 H4k*H2 H4l*H2 G1 Ttaalb Ttaalc;
run;
```

Generalized Estimating Equations (GEE)

```
/***Weighted GEE**/
/***Final model after applying the macro that does the weighting**/
proc genmod data=thesisw descending;
weight wi;
class hospcode A0 H4 Ttaal ;
model ops1 = A0 H1 H3 H4 H6 G1 Ttaal /  dist=binomial type3;
repeated subject=hospcode / type=un subclust=A0;
run;
```

```
/**MI+GEE**/
/*first step imputation to produce monotone missingness*/
proc MI data=thesis nimpute=5 seed=33 out=outimputed;
var A0 H4 Ttaal hospcode H1 H3 H6 G1 ops1;
mcmc impute=monotone;run;
/*2nd step imputation for the remaining variables after 1st step*/
proc MI  nimpute=5 data=outimputed out=outimpute2 seed=333;
class  A0 H4 Ttaal hospcode;
var  A0 H4 Ttaal hospcode H1 H3 H6 G1 ops1;
monotone regression (H1= A0 H4 Ttaal hospcode);
monotone regression (H3= A0 H4 Ttaal hospcode H1);
monotone regression (H6= A0 H4 Ttaal hospcode H1 H3);
monotone regression (G1= A0 H4 Ttaal hospcode H1 H3 H6);
monotone logistic (ops1= A0 H4 Ttaal hospcode H1 H3 H6 G1);
run;

/*Analysis of the 5 new data sets*/
proc genmod data=outimpute2 descending;
by _imputation_;
class hospcode ;
model ops1 = A0 H1 H3 H4 H6 G1 A0a A0c A0d A0e A0f A0g A0h A0i A0j A0k A0l
A0m A0n H4b H4c H4d H4e H4f H4g H4h H4i H4j H4k H4l Ttaalb Ttaalc  /
dist=binomial type3;
repeated subject=hospcode / type=un subclust=A0;
ods output GEEEmpPEst=miparms parminfo=miparminf;
run;

proc mianalyze parms=miparms parminfo=miparminf;
modeleffects intercept H1 H3 H6 G1 A0a A0c A0d A0e A0f A0g A0h A0i A0j A0k
A0l A0m A0n H4b H4c H4d H4e H4f H4g H4h H4i H4j H4k H4l G1 Ttaalb Ttaalc  ;
run;
```

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Richting: **Master of Statistics-Biostatistics**
Jaar: **2011**

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